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Achieving Universal Electricity Access at the Lowest Cost

A comparison of least-cost electrification models

James Morrissey

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CONTENTS

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Author information and acknowledgments

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ACRONYMS AND ABBREVIATIONS

AfDB	African Development Bank
BOS	balance of system
HV	high voltage
IEA	International Energy Agency
IRENA	International Renewable Energy Agency
km	kilometer
KTH	Royal Institute of Technology at Stockholm
kV	kilovolt
kVA	kilovolt-amp
kW	kilowatt
kWh	kilowatt-hour
kWp	kilowatt peak
LCEM	least-cost electrification model
LCOE	levelized cost of electricity
LV	low voltage
MV	medium voltage
MWh	megawatt-hour
O&M	operation and maintenance
OSM	OpenStreetMap
PV	photovoltaics

EXECUTIVE SUMMARY

Achieving universal access to electricity remains a firm ambition of the Sustainable Development Goals. Progress toward this goal has benefited from the recent decline in the cost of renewable energy technologies. Because of their modularity, these technologies have created new opportunities to supply households with affordable electricity based on the use of distributed electricity generation. However, these new technologies have created challenges for electrification planning. Whereas grid expansion would previously have been planned for all households, now effective planning involves assessing which technology option (grid expansion or one of a variety of distributed generation sources) can provide the necessary energy services to each household at the lowest cost.

To meet this challenge, a number of models have been built that aim to describe the appropriate technology allocation for achieving universal access to electricity at the lowest total cost. These models seek to account for the different capital and generation costs of different technologies, allowing for variability in these costs in both space and time. For the purposes of this report, these models have been termed least-cost electrification models (LCEMs).

While LCEMs provide a new and important tool for policy makers, questions remain about their accuracy. Such questions are increasingly pertinent given that these models are built on data that is known to be poor and that computational challenges for the models require that they invoke significant simplifications.

To address these questions, this report reviews the published results from 23 different papers based on the workings of a variety of LCEMs. In so doing, this work seeks to understand the variability in model findings on the grounds that significant variability suggests challenges for accuracy. With this in mind, the report does the following:

1. It summarizes the workings of the models used in different publications, describing their overall logic as well as how they deal with data issues and overcome computational challenges. The intent is to make clear both the dynamics shaping least-cost electrification options and to highlight potential sources of variance across the models.

2. It identifies areas of work for modelers and calls for a push to generate comparable findings and to investigate sources of variance across models.

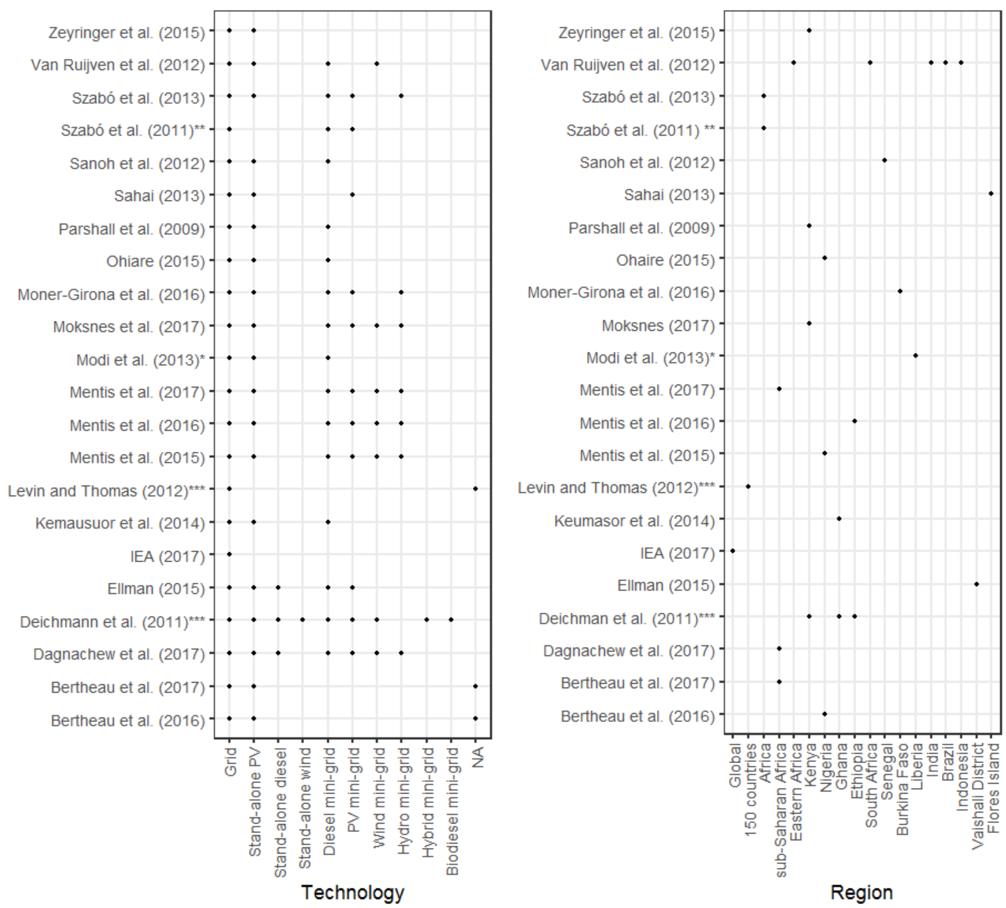
3. It attempts to compare the findings of the models in order to determine the level of agreement across them. This is achieved by controlling for the level of demand assumed by the different models and by assessing the level of

agreement across them. The level of agreement is assessed considering the least-cost allocation (i) between grid and distributed technologies as well as (ii) between mini-grids and stand-alone systems.

4. Given the limited claims that can be made about the accuracy of these models, determined by 3, it cautions against advocates using the findings of these models too simplistically.

Despite the efforts made to render these results comparable, efforts at a systematic comparison are fraught given the multiple differences between models. Of particular relevance are the different technologies considered as well as the different geographies to which the models are applied (see Figure E1).

Figure E1. Differences in technology and geography across studies



Source: Author

Notes: NA = not available.

* Not included in Figure E2/5 as they did not compute LCEM for 100 percent access.

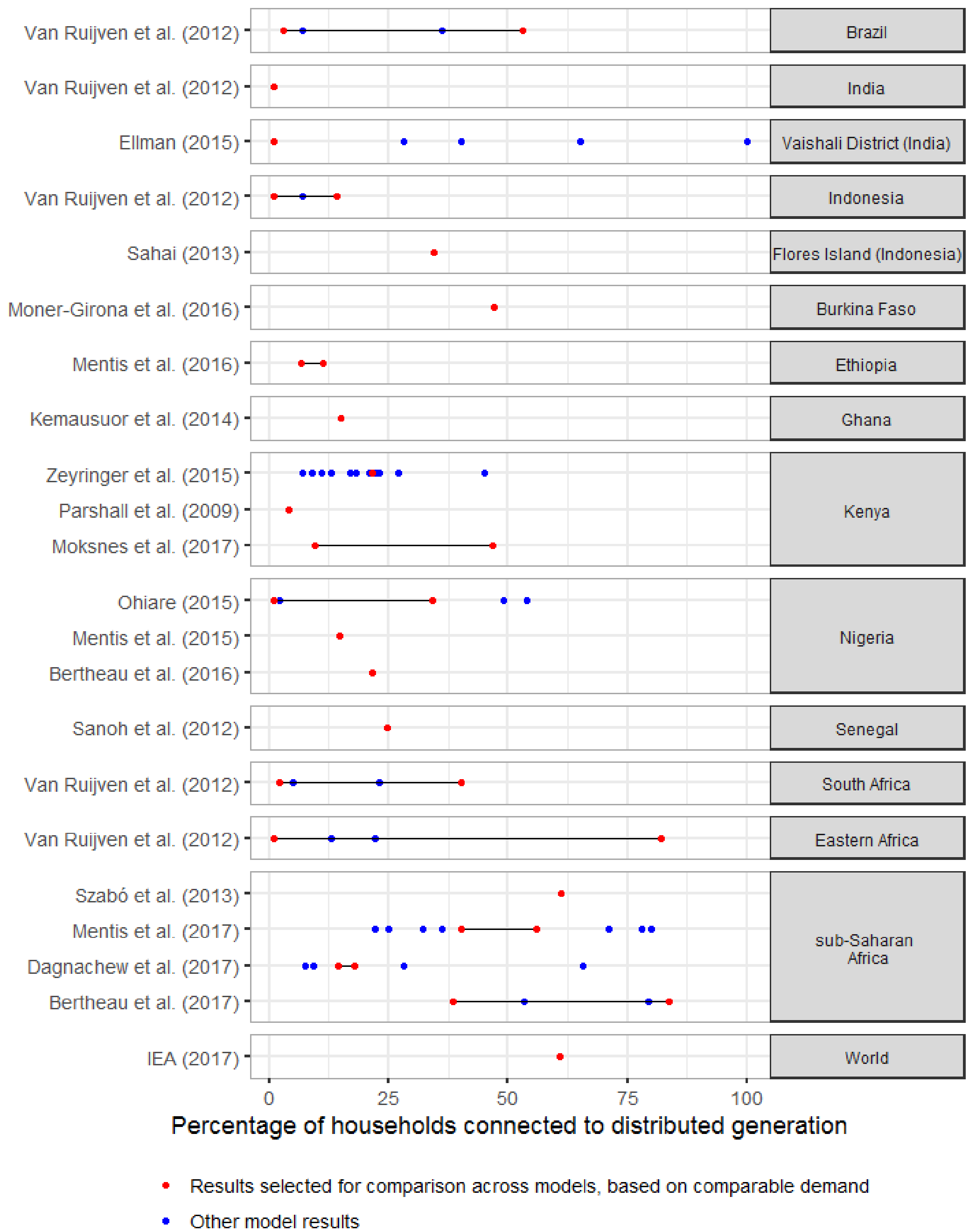
** Not included in Figure E2/5 as they did not provide explicit results comparing grid versus distributed generation.

*** Not included in Figure 4 as they calculate the grid from scratch, ignoring any existing grid network.

The results indicate significant variability across both models and geographies (see Figure E2):

1. Across **models and geographies,** results range widely, showing that between 1 and 82 percent of the unconnected population will be connected most cheaply using distributed generation technologies.
2. Within **countries and regions** with more than one published model result, ranges are also large. Results range from 4 percent to 47 percent in Kenya, from 1 percent to 34 percent in Nigeria, and from 18 percent to 79 percent across sub-Saharan Africa.
3. Even **within results for the same model,** the range can be large across comparable demand scenarios. For example Van Ruijven et al. (2012), considering East Africa, finds that distributed technology allocations are cheapest for anywhere between 1 and 82 percent of the population, depending on the investment costs used.
4. Further, considering the variety of results within each model (blue points in Figure E2), it is clear that varying demand across models makes a huge difference in terms of technology allocation.

Figure E2. Comparison results across LCEMs estimating technology allocation for universal electricity access



Note: Published findings are grouped by the country or region modeled. Results control for demand (between tiers 2 and tier 4 of the World Bank Multi-Tier Framework for measuring energy access; see Table 4 in the main report) for details. Red dots in the figure refer to scenarios using comparable demand (between tiers 2 and 4). In cases with multiple red dots, more than one scenario uses the same level of demand—for example, varying investment costs while keeping demand constant. Blue dots represent other results from the model, accounting for other levels of demand. The figure ignores results from sensitivity tests.

Reasons for such variability stem from

1. The variety of computational logics adopted by different models;
2. The different ways different models address missing data;
3. The different simplifications different models adopt in order to overcome the computational intensity that would be involved in determining ideal technology allocations; and
4. The different technologies assessed by different models (see Figure E1).

The different computational logics are specific to each model, and their differences are not easily classified. For data quality issues, the main challenges relate to the location of the existing grid, the locations of currently unelectrified households, the latent demand among currently unelectrified households, and the capital costs of energy infrastructure. Regarding computational complexity, differences relate to how models optimize the length of the grid network, how they cluster households into settlements that can be connected by larger pieces of infrastructure, and whether and how they address the dynamic manner in which (1) extending the grid results in subsequently reduced costs for further grid extension, and (2) connecting households to the grid changes the subsequent cost-reflective grid tariff.

Variable model results also suggest that the individual countries that have been modeled are not representative of the larger regions of which they are a part. For example, published findings on Burkina Faso, Ethiopia, Ghana, Kenya, Nigeria, Senegal, and South Africa—which present 15 possible model results—all suggest that *less* than 50 percent of new connections would come from distributed technologies, while for the sub-Saharan African region just under half of the comparable results (3 out of 7) predict that *more* than 50 percent of the population would be most cheaply connected by distributed technologies. This is not an impossible outcome: the individual countries modeled here account for only about 30 percent of the currently unelectrified population. That said, if the models are accurate, they show that the countries selected for modeling represent exceptional cases. Finally, across the models, findings on the role of stand-alone versus mini-grid generation systems (though not indicated in Figures E1 and E2) are confounding:

1. Models built for specific sub-Saharan African countries tend to indicate a larger role for mini-grids than for stand-alone systems.
2. Models built for the sub-Saharan African region indicate a larger role for stand-alone systems than for mini-grids.

3. Models built for the global level, which use a similar modeling approach to the models used for the regional assessment, indicate a larger role for mini-grids than for stand-alone systems.

It is possible to explain these findings on the grounds that the smaller geographies are not indicative of the larger regions they constitute. This explanation is contradicted, however, by what the models might be expected to predict in terms of the on-grid, off-grid split. Moreover, differences of this sort should raise concerns given that country models are generally based on better data than regional and global models.

Such variability notwithstanding, the findings across models suggest agreement on the following:

1. For large geographical areas (even if not for the majority of the population), distributed generation technologies will be cheapest.

2. There will be little role for micro-hydro in achieving universal access to electricity even though micro-hydro can generate electricity at relatively low prices compared with other distributed systems.

This analysis, it should be noted, suffers from significant limitations. First, different models use different parameters, making easy comparison impossible. Second, the number of models considering the same geographic region is small, so samples for comparison are small. Given that this was an effort to consider all known published results of LCEMs, the large variance in findings across both models and geographies suggests that **policy makers and advocates should exercise significant caution when citing the findings of different models as the basis for planning or investment**. When advocating for specific policies, policy makers and advocates should seek to identify multiple models and avoid citing models that do not publish their methods. A particularly salient case of this is the IEA model, which is widely cited and publishes only a limited account of its method.

When advocating at the regional level, policy makers and advocates should seek to identify exactly which countries are being included in models in order to account for high levels of variability across countries. Overall, rather than using models to advocate for the split between grid extension and distributed generation, it would be more productive to use them to inform the geographic regions where particular technologies will be most competitive. There appears to be far more agreement across models regarding broad geographic trends than there is regarding the proportion of the population that should be connected to which technology.

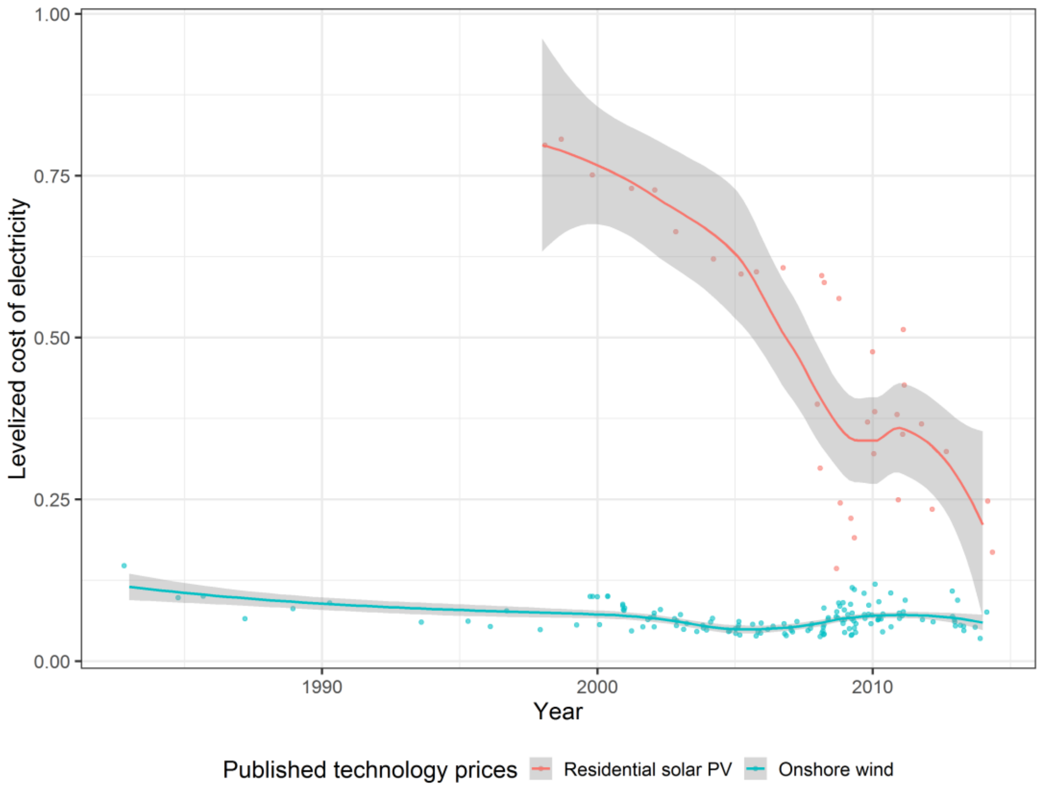
For modelers, the high levels of variability across models suggest that there is value in devoting greater effort to testing the impact of different modeling logics, algorithms, and data sets in order to determine their impact on variability. Regarding the geographic variability of results, while there is certainly value in models using country-specific parameters (which are likely to provide greater accuracy), there would be additional value in including a generic set of parameters that allow for comparison across models. Fundamentally, models should seek to ensure that their parameters and logics are published and are open access, so that sources of variance across models can be identified.

INTRODUCTION

The goal of achieving universal access to electricity has received increasing attention in recent years. Historically, this process has relied on grid expansion for which planning processes are well established: incrementally extend the grid on a least-cost basis, prioritizing areas that are cheapest to connect and likely to generate the largest revenues for the utility. While this approach has been successful in electrifying most of the world to date, it is a slow, capital-intensive process in which, in the aggregate, those households that are wealthiest and closest to existing infrastructure get connected first, while the poorest and most remote populations are connected last.

With the advent of cheap, modular renewables (see Figure 1), there is increasing scope to provide access to electricity through distributed generation sources, which, rather than generating power centrally and distributing it through the grid, generate power much closer to the site where it will be consumed. Such systems include mini-grids and stand-alone systems; while these vary in size, they are distinguished by the fact that they are not connected to the national grid. While these technologies have created new momentum around electrification, with the potential to connect poor remote populations more quickly and with fewer capital risks, they have also raised new challenges for planning. Such technology choices force the questions: which households should be connected to the grid, which households should be connected to distributed systems, and what scale of resources should actors concerned with universal electricity access be devoting to each technology?

Figure 1. Declining costs of renewables



Source: Open EI (2018).

Answering these questions is not a straightforward task. While there is general agreement that a least-cost approach should be pursued,[1] the determinants of the cost of electrification for any household differ by technology, and the inputs for determining the cost of any technology vary in both space and time. Given that about 200 million households globally currently lack access to electricity,[2] the computational challenges of determining the least-cost technology allocation for achieving universal energy access are substantial. All of these challenges are made significantly more difficult when one considers that data are either poor or nonexistent for many of the parameters necessary for undertaking a least-cost assessment.

Despite the challenges involved in such an assessment, a number of authors and institutes have built models to estimate the technology allocation that would achieve universal access to electricity at the lowest cost. For the purpose of this

[1] Although this is true as a general statement, the speed with which distributed technologies can be deployed, as well as the potential role for the private sector to get around problems of financially unsustainable utilities, should not be underestimated.

[2] This figure is calculated using the IEA number of 1.06 billion individuals and assuming five people per household (IEA 2017a).

study, these models are called least-cost electrification models (LCEMs). LCEMs take advantage of newly available remotely sensed data in order to address data constraints and are anticipated to be particularly useful to policy makers because their findings can be visualized spatially and therefore effectively communicated (Szabó et al. 2011; Szabó et al. 2013; Mentis et al. 2015, 2016).

Notably, findings from these models have been picked up by both policy makers and advocates. In some cases national governments have collaborated in the development of models (Modi et al. 2013; Moner-Girona et al. 2016), while in other cases governments have contacted the academic institutions building these models, seeking to incorporate their findings into policy making (M. Moner-Girona, personal communication, January 15, 2019). At the same time, energy access advocates have picked up on model results that show a large role for distributed generation technologies as the least-cost means for achieving universal energy access—most notably the findings of the IEA's modeling efforts (Sierra Club and Oil Change International 2014).

Considering the apparent influence of LCEMs on both policy and advocacy, it is useful to take a closer look at their accuracy. This report assesses 23 different published results from a variety of LCEMs and compares their findings.[3] The aim of this review is to assess the level of variability that exists across both geographies and models (where the same geography has been modeled using multiple LCEMs). In doing so, the report intends to describe the levels of agreement that exist across published model results as well as the extent to which model findings are generalizable across geographies. Further, by exploring and describing the specific computational logic of different models, the report aims to increase understanding among policy makers and advocates regarding the determinants of least-cost technology allocation when pursuing electrification.

It should be noted that this report compares published model findings, but it does not compare the actual models or the possibilities for running them with different parameters. The latter task was beyond the scope of this review, in part because not all researchers publish the manual and/or source code for their models. Potential modelers looking to improve upon the functioning of specific models will have to consult these documents in greater detail in order to advance this field.

The report finds that there is currently limited ability to compare model findings across contexts and thus limited scope to assess the accuracy of different models. To the extent that we can undertake a comparison across models, the results reveal significant variability, both across models and across geographies. Such conclusions suggest important caveats for policy makers and advocates

[3] These publications were identified by internet searches of the literature, subsequent snowballing of references, and interviews with authors of LCEMs. It is possible that this review missed other existing models and publications, but because of the relatively small nature of the modeling community—which is often clustered in research centers with a specific focus on this issue—the number of missed publications is expected to be small. The obvious exception to this, of course, consists of unpublished modeling exercises carried out by governments and consultancies.

seeking to use the outputs of models. Further, there appears to be valuable work to be done by modelers to quantify the sources of variability across models and to develop better uniform proxies and computational logics so as to generate more accurate, and therefore more useful, models to support policy makers and advocates. The report and its findings contribute to the existing literature as the first review that compares model findings and explicitly discusses the contrasting computational logics to try to explain model variability. Although other reviews of the literature do exist, they focus on classifying the broad types of energy planning literature (Trotter, McManus, and Maconachie 2017), identifying what different models are capable of incorporating (Cader, Blechinger, and Bertheau 2016), or describing the extent to which they integrate concerns related to achieving SDG 7 (on energy) (Moner-Girona et al. 2018). Notably, none of these reviews seek to document and explain the variability in model results. The closest effort comes from a doctoral thesis that describes different modeling efforts but does not seek to determine the level of (dis)agreement in published results (Mentis 2017).[4]

With this context in mind, this report begins by explaining in greater detail what LCEMs are and why they are necessary. It also introduces the notion of the levelized cost of electricity (LCOE) as applied in an energy delivery context, as this is the basis upon which LCEMs allocate different technologies. Next the report discusses the necessary inputs for calculating the LCOE, the challenges in attaining these data, and how different models solve these challenges. It goes on to discuss the computational challenges inherent in the different LCEMs and how these are resolved. Notably, the report is dominated by the sections on data inputs and computational logic because these are central to explaining potential sources of variability in the models. The report then analyzes the variability across models, and it concludes with a discussion of what such variability means for both policy makers and modelers. The appendix provides a detailed account of every published model result assessed as part of this work.

[4] The relevant discussion appears in a chapter titled “GIS and Energy Planning.”

MODELS: HOW AND WHY

COPING WITH COMPLEXITY AND TRADE-OFFS

For any household or settlement, the least-cost technology choice for electrification depends upon multiple factors that interact dynamically and are too numerous to calculate without extensive computation. This, in the most general terms, is why models are needed to determine the least-cost electrification pathway for a country or region. Moreover, because the drivers of electrification costs vary spatially (and to a lesser extent temporally[5]), models need to be spatially and temporally explicit, adding to the computational intensity of the task.

There are trade-offs involved in choosing among technologies to achieve electrification at the lowest cost. On the one hand, whereas the grid can generally generate electricity at a lower unit cost ($/kilowatt-hour[6]) than distributed technologies, building out the grid to deliver that electricity to households is expensive. On the other hand, although distributed generation has high generation costs and thus higher unit costs for electricity, generation is on site, eliminating the need for expensive transmission infrastructure. Additionally, the cost of providing distributed generation is largely independent of the remoteness of a household.[7] Thus, for households that either consume very small amounts of electricity or are remote from the existing grid (or both), the overall cost of consuming more expensive electricity from distributed sources is likely offset by the savings generated by not having to extend the grid. On the other hand, in areas where demand is high or where populations are close to the existing grid (or both), the high cost of grid extension is justified by the savings generated on every individual kWh of electricity consumed.

The fundamental question for least-cost electrification models therefore is: what proportion of the population is (in)sufficiently far from the grid, of (in)sufficiently low density, and/or consuming a (in)sufficiently small amount of electricity to be connected most cheaply with (the grid or) distributed generation technologies? A first step in being able to estimate these costs is establishing a metric for comparing the costs of different electricity generation and delivery technologies.

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[5] Note that the temporal dimensions of least-cost electrification are becoming more important because models need to account for the declining costs of renewables. Although a few models do this, most ignore this process and operate with a single time step (see section on computational challenges below).

[6] A kilowatt-hour (kWh) is the amount of energy produced by a generation source with a power output of 1 kW when that source is run for one hour. Thus a 1 kW solar panel running for one hour will produce 1 kWh of energy.

[7] The exception is distributed diesel generation. The costs of supplying diesel vary spatially, and how different models address this issue is discussed below. Furthermore, someone must still service these generators, so maintenance and installation costs likely increase in more remote areas, but these increases are much smaller than the cost of building out the grid.

TECHNOLOGY SELECTION USING THE LOWEST LEVELIZED COST OF ELECTRICITY

Each LCEM reviewed in this report invokes a specific set of logical sequences by which the cheapest technology is selected (the specific logic of each model is discussed more fully in the Appendix). Across all of the models, however, the idea of the levelized cost of electricity (LCOE) is central: technologies are selected based on having the lowest levelized cost. LCOE is calculated by adding up the costs of capital, fuel, operation and maintenance (O&M), and salvage and dividing this amount by the total energy produced by that generator over its entire lifetime. A discount rate must also be applied to account for the fact that money spent on the generator now drives electricity consumption that will take place in the future. This calculation results in an LCOE expressed as a currency-specific cost per kilowatt-hour ($/kWh).

Using LCOE to derive delivery costs, however, calls for a slightly different approach. Rather than focusing on how much energy a system can generate—based on its capacity—the focus is on how much *demand* the system can meet. This is important for a number of reasons:

1. In the case of intermittent, renewable generation, the system must be able to meet demand as it arises, and not only when the renewable resource is available. This results in increased capital costs in the form of batteries or complementary fossil fuels, and these costs need to be accounted for.
2. When a system serves an increasingly diverse set of users (such as a whole settlement rather than a household), the peak demand placed on the system is less than the sum of peak demand from each user – a result caused by each user placing their peak demand on the system at slightly different times. This means that generation systems serving more diverse demand (i.e., more people) can have a reduced capacity and therefore reduced capital costs. LCOE calculations focused on meeting demand can show the reduced unit costs for electricity that can be achieved by connecting multiple households to single pieces of infrastructure, such as mini-grids or the grid.
3. In the case of the grid, which can deliver large amounts of electricity (far more than could be feasibly used by a low-income household), a focus on capacity would drive the LCOE to very low levels. However, because households only need a specific amount of energy, it makes sense to consider the cost of meeting only that demand.

Finally, in addition to focusing on demand met, in the case of the grid and mini-grids the LCOE for delivering energy needs to include the costs of distribution infrastructure, and, in the latter case, transmission infrastructure—neither of which is necessary in the case of stand-alone systems (see box).

Calculating LCOEs for different technologies

Below is a general account of how LCEMs calculate the costs of different technologies that commonly appear in LCEMs: stand-alone solar and diesel-based systems; wind, diesel, hydroelectric, and solar mini-grids; and the grid.

Stand-Alone Systems

Stand-alone systems refer to generation systems that supply a single consumer. These systems require no energy delivery infrastructure and therefore have no capital costs for transmission or distribution. For **stand-alone diesel systems,** which are dispatchable, this means that the LCOE calculation for energy delivery is identical to the LCOE calculation for the generator's capacity. The LCOE calculation thus includes the capital costs of the generator, operation and maintenance (O&M) costs, and salvage costs, and the result is determined by the cost of fuel and the efficiency of the generator.

For **stand-alone solar systems** the cost is determined by the capital cost of the solar panels and balance of system (BOS) components, as well as the O&M and salvage costs. Because solar is an intermittent energy source, the system also requires a battery. The size of the battery must be set so that the system is capable of delivering energy when it is needed, with an acceptable level of reliability based on an assessment of the solar resource potential and its temporal variability. The battery size must also account for issues of depth of discharge in providing such reliability, considering what this means for the lifespan of the battery. Of course the size of the solar generator must be sufficient not only to meet peak demand, but also to ensure that the battery remains sufficiently charged to provide reliable energy without discharging the battery too deeply.

Mini-Grids

Mini-grids refer to small clusters of energy consumers who are linked up to one or multiple generating sources. Although mini-grids are themselves grids, they are considered distributed sources because they operate independently of the national grid.[8] **Solar, diesel, and wind-based mini-grids** include the same costs as stand-alone systems, plus the cost of distribution infrastructure. This distribution cost is usually estimated based on the established capital, O&M, and salvage costs of low-voltage (LV) power lines. Additionally, if the goal is to integrate solar mini-grids with the grid in the future, these systems need to include inverters so that the DC current they generate can flow into the main grid. For **hydroelectric mini-grids** the costs include generation and distribution infrastructure, as well as transmission costs of transporting electricity from the generator (which must be located on a suitable body of water) to the settlement it is intended to serve. Again, this cost is usually based on the cost of LV power lines; it can also include the cost of transformers, depending on the

[8] Different models use different definitions of what size grid qualifies as a mini-grid. For the purposes of this report, the definitions used in published studies were simply accepted.

generation capacity of the system and how far the settlement is from the generating source. Notably, generation sources on mini-grids can be combined to form hybrid systems. This is useful for addressing the intermittency of wind and solar systems and for limiting the high cost of batteries by replacing them with diesel.[9]

Grid

For the grid, costs are driven by the cost of generating electricity on the grid (or the cost-reflective tariff) plus the costs of transmission and distribution, including the costs of any transformers.

Although all electrification systems involve costs for wiring the newly connected infrastructure, these costs are usually ignored in the case of LCEMs because they are common to all systems and thus do not affect the selection of the least-cost system.

While the general account of LCOE as the driver of LCEMs places the focus firmly on demand, a number of models described in this review are able to avoid a focus on demand in estimating LCOE. They do this either (1) by using population density as a proxy for demand or (2) by assuming standard capacities for the generators considered in the model and then calculating the LCOE for those systems as they appear in the model.

When using the first approach—population density as a proxy for demand—the models assume that populations located within some predetermined distance from the grid will be connected most cheaply by the grid, while populations beyond this distance will be connected most cheaply by distributed generation. Further, the models assume that population centers of a certain size will be most cheaply connected by mini-grids while centers below a certain size will be most cheaply connected with stand-alone systems (Bertheau, Cader, and Blechinger 2016; Bertheau et al. 2017).

In the second approach—assuming a standard capacity for a generator—the models assume a cutoff for what would be considered an acceptable LCOE. It then maps where different generators can meet that LCOE, based on resource availability and fuel costs. Like the first approach focused on population density, the approach using standard capacities for generators deals with grid connections by assuming that all households within a certain distance of the existing grid will be connected most cheaply by the grid (Szabó et al. 2011).

Outside of these two simplified approaches, LCEMs generally seek to calculate the LCOE for each technology being assessed for each household—though households are usually grouped into demand nodes composed of settlements or

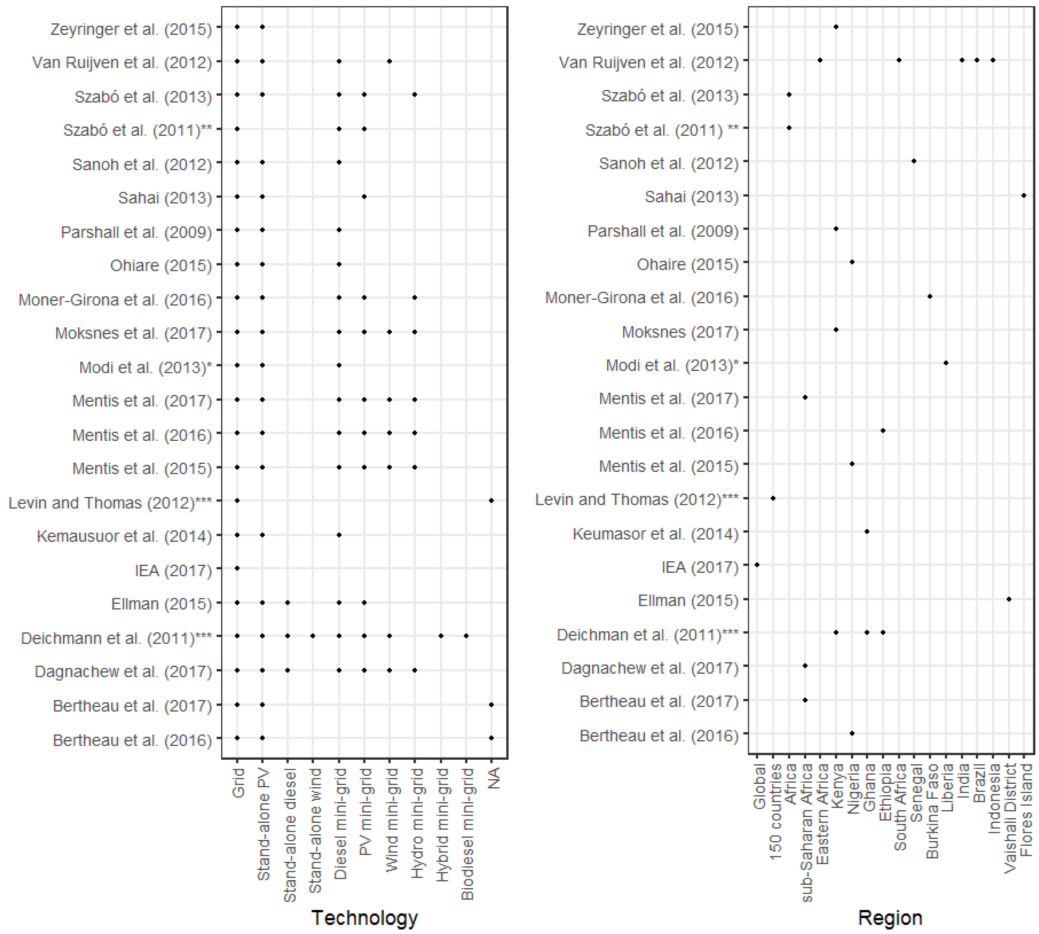
[9] Although diesel generators might be cheaper than batteries when fuel costs are low, relying on diesel for mini-grids raises its own challenges with regard to the potential instability of the diesel supply chain (Morrissey 2017).

grid cells of average population density (more details below). Based on the lowest LCOE, the models allocate a technology to each demand node.

The exact inputs needed for producing an LCEM depend on the technologies being considered, and since inputs are spatially explicit, model results will differ by geography. Different models consider a wide variety of different generating technologies and geographies (see Figure 2 and Table 5). Almost all models consider the grid and either stand-alone or mini-grid solar photovoltaics (PV). Most consider the grid, solar PV, and diesel (accounting for both stand-alone systems and mini-grids). Some models include a large variety of generating sources: grid, solar PV, diesel, wind, biomass, and mini-hydro, including all possible renewable-diesel hybrid combinations.

The geographic variation across models is likewise significant, including subnational, national, regional, and global assessments. Sub-Saharan African countries dominate because that region suffers from the most acute energy access challenges. Within this, Kenya and Nigeria dominate, along with regional assessments of sub-Saharan Africa. The use of different technologies and a variety of geographies presents a significant challenge for comparisons of published results.

Figure 2. Differences in technology and geography across studies



Source: Author
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ESTIMATING MODEL INPUTS

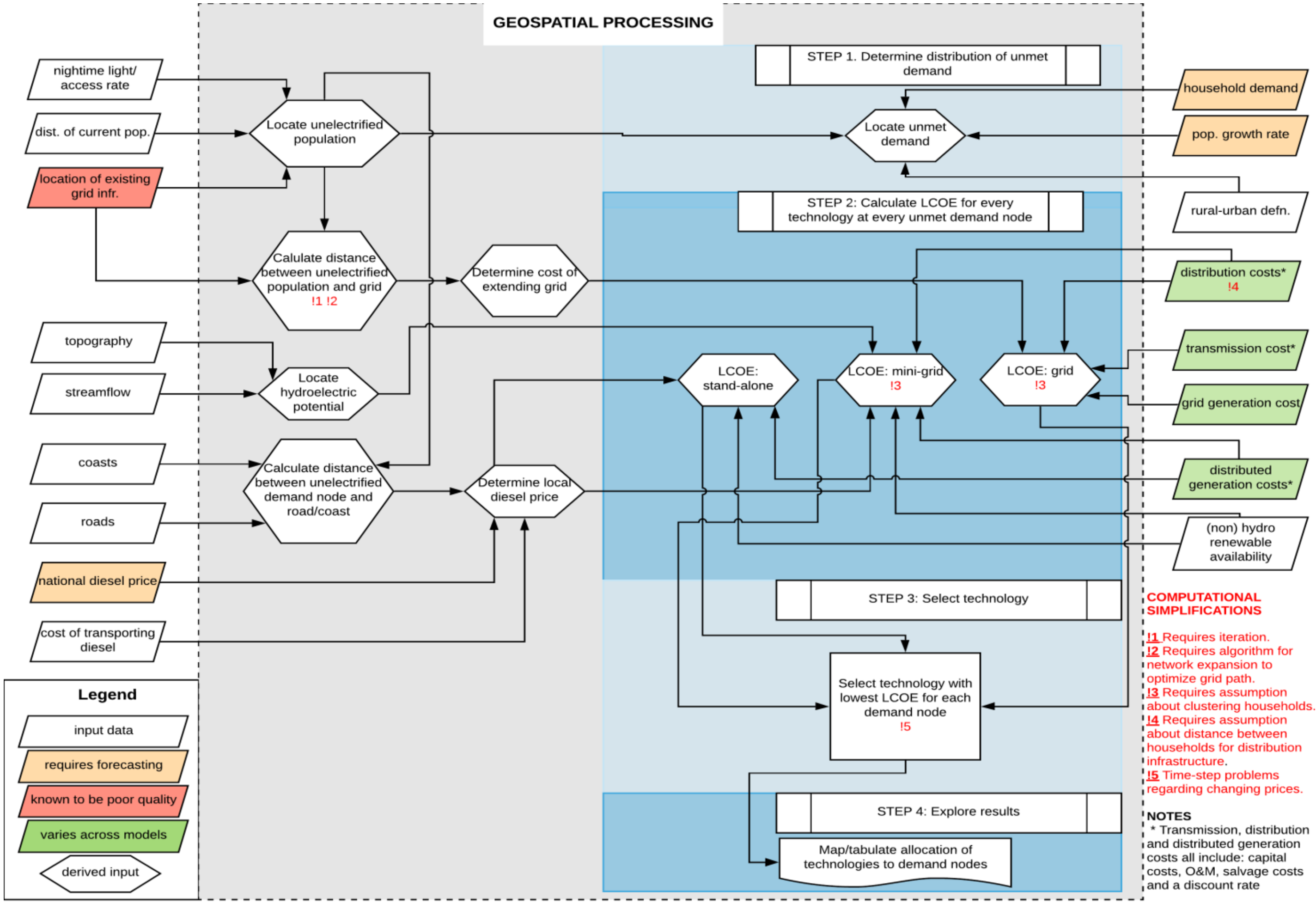
With a general understanding of how LCEMs work, it is possible to describe the different inputs necessary to calculate the LCOE (Figure 3). These include

1. The geolocation of the existing grid;
2. The geolocation of unelectrified households;
3. The latent demand of unelectrified households;
4. The spatial distribution of renewable energy availability;
5. Diesel costs (possibly including an assessment of how price varies spatially);
6. The cost-reflective tariff for grid electricity; and
7. Capital, O&M, and salvage costs for generating technologies, as well as infrastructure for transmission (relevant for the grid) and distribution (relevant for the grid and mini-grid).

Further, because most models seek to address energy demand at some point in the future, they need to account for factors that will change in the model over time. These include

1. Population growth, which increases demand on the overall system as well as within any settlement;
2. Increasing household demand, because connected households tend to increase their consumption over time;
3. Future diesel prices; and
4. Future declines in capital costs, especially as these pertain to renewable energy components.

Figure 3. Schematic showing inputs, general logic, and sources of variability within LCEMs



Source: Author.

Assuming one has all of the inputs described above, the task of modeling the selection of the least-cost technology is largely manageable (save for some computational challenges, which will be discussed below). In reality, though, attaining data on these inputs can be challenging. In countries with low electricity access rates, the data needed to build an LCEM are usually not stored in a single database, or anywhere at all (S. Szabó et al. 2013; Mentis et al. 2015). As a result, LCEMs must frequently estimate input data. LCEMs have recently gained prominence not only owing to the reduced cost of renewable components and the potential for distributed generation, but also because of advances in the use of remotely sensed data to attain the relevant inputs. Even with these advances, data problems remain significant, and the different ways they are solved are a source of variance in the model results.

LOCATING THE EXTENT OF THE EXISTING GRID

The specific geolocation of existing grid infrastructure is usually determined from existing data sets. These data must be specified to include the different components of the grid, such as the voltage of particular power lines, the location of substations, and the capacities of transformers. For models being developed at the national level, it is often possible to use data held by the national utility (Parshall et al. 2009; Sanoh et al. 2012; Modi et al. 2013; Sahai 2013), though the quality of these data can vary. Otherwise two data sets dominate: (1) the OpenStreetMap (OSM), Infrastructure – Power Map, and (2) the Infrastructure Map from the African Development Bank (AfDB) from 2011.[10] The AfDB map applies only to Africa, but given the low rates of electrification in that region, Africa is the focus of many LCEMs and thus this data set is commonly used.

Despite the value provided by the OSM and AfDB data sets, it is important to appreciate the extent to which they are incomplete. The following quote from the World Bank describes the *updated* energy infrastructure map for the Africa Infrastructure Country Diagnostic, which is compiled from multiple sources, including OpenStreetMap and is considered the “most complete and up-to-date open map of Africa's electricity grid network” (Energydata.info n.d.):

> Some of the data, notably that from the AICD [Africa Infrastructure Country Diagnostic] and from World Bank project archives, may be very out of date. Where possible this has been improved with data from other sources, but in many cases this wasn't possible. This varies significantly from country to country, depending on data availability. Thus, many new lines may exist which aren't

[10] Future models will likely be updated to use the Africa Infrastructure Country Diagnostic map from 2017.

shown, and planned lines may have completely changed or already been constructed (Energydata.info n.d.)

The incomplete nature of this data set creates significant problems for LCEMs. This is because the cost of extending the grid is extremely large (see Table 2), and thus the distance between an existing settlement and the grid is a core driver of LCOE.

Different models seek to address this problem to different extents, principally through triangulation with other data sets, including interviews with national utilities and other agencies (Szabó et al. 2011; Szabó et al. 2013; Bertheau et al. 2017). Triangulation is obviously easier for models being applied to smaller geographies, but for regional models the constraints of such poor grid data are significant. Nonetheless, these data gaps are often simply ignored, with many models relying solely on either the AfDB (Mentis et al. 2015, 2016) or OSM map (Van Ruijven, Schers, and van Vuuren 2012; Dagnachew et al. 2017; Zeyringer et al. 2015). Because errors in the grid data set are likely to fail to document the grid where it exists rather than showing it where it does not exist, these errors are likely to result in an underestimation of the extent to which grid connections are the cheapest technology; models will generate larger distances between the existing grid and unconnected households, resulting in higher transmission costs and therefore larger LCOE values for the grid.

Beyond databases on grid infrastructure, models have made use of nighttime illumination data, which can identify electrified areas by measuring the light they emit into space overnight (Bertheau, Cader, and Blechinger 2016). In some cases this approach has been paired with the infrastructure maps as a means of triangulation (Mentis et al. 2017). Because this approach assumes that areas emitting light are connected to the grid, it estimates grid extent based on proximity to illuminated settlements.

For subnational analyses a final option is to use aerial photography to identify electricity infrastructure (e.g., Ellman 2015). The challenge with this approach is that it is still able to capture only medium-voltage infrastructure rather than the low-voltage lines that connect households. Further, processing the aerial photography creates challenges that efforts at machine learning have had little success in resolving (Ellman 2015).

Besides using different data sources to locate existing grid infrastructure, models differ in whether they consider only the existing grid (Modi et al. 2013; Zeyringer et al. 2015) or include planned grid construction (Szabó et al. 2013; Moner-Girona et al. 2017; Bertheau et al. 2017; Mentis et al. 2015, 2016, 2017). Researchers sometimes incorporate planned grid construction directly by using formal plans from relevant agencies (Szabó et al. 2013; Bertheau et al. 2017; Moner-Girona et al. 2017) or by relying on knowledge of large mineral-rich areas (derived most often from the US Geological Survey). Mining is anticipated in those areas, which are therefore expected to be connected to the grid in the future (Mentis et al. 2015, 2016, 2017).

IDENTIFYING UNCONNECTED HOUSEHOLDS

For most countries with low electrification rates, data sets detailing the exact location of unconnected households do not exist. This information must be inferred from other data sets.

Most large-scale modeling efforts begin with high-resolution population density maps,[11] which tend to take one of three forms:

1. A geospatial grid, with average population density for each grid cell (raster data);
2. A set of geolocated settlements, which present as points (i.e., they have no spatial extent) with information on population size for each settlement; or
3. A combination of the above whereby the model begins with an administrative area and then makes assumptions about the percentage of that area that might be inhabited (Parshall et al. 2009).

Data on population tends to come from the following sources:

1. the Socioeconomic Data and Applications Center (SEDAC)12 (Moksnes et al. 2017; Szabó et al. 2013; Van Ruijven, Schers, and van Vuuren 2012; Dagnachew et al. 2017; Levin and Thomas 2012);
2. other large data sets such as Linard et al. (2012) (Mentis et al. 2016);
3. WorldPop (Mentis et al. 2017); or
4. census data or other local data sources (Parshall et al. 2009; Sanoh et al. 2012; Modi et al. 2013; Kemausuor et al. 2014; Ohiare 2015; Moner-Girona et al. 2017; Bertheau et al. 2017; Bertheau, Cader, and Blechinger 2016; Ellman 2015).

Regardless of the data set used, two approaches exist to locate the unconnected population. The first is to look at information on electrification rates and assume that all people who are electrified live in relatively close proximity to the existing grid. Based on this assumption, the model creates a buffer around the grid, expanding the size of the buffer until it contains the number of dwellings or people (depending on the population data set used) believed to be electrified in the geography being modeled (Van Ruijven, Schers, and van Vuuren 2012; Mentis et al. 2015, 2016; Dagnachew et al. 2017). This approach is likely to bias

[11] As with grid extent, different models undertake efforts at triangulation, or seek to address issues of missing data, to different extents, by combining different data sets.

[12] SEDAC is run by US National Aeronautics and Space Administration (NASA) and hosted by the Center for International Earth Science Information Network (CIESIN) at Columbia University.

the model findings toward off-grid technologies by underestimating the geographical extent of existing, connected households, given that grid connections do not radiate uniformly from the grid.

The second approach is to use remotely sensed nighttime illumination data. This approach overlays population density data or settlement data onto nighttime illumination data to determine the number of unelectrified people/dwellings based on the number of people living in areas without nighttime illumination (Bertheau, Cader, and Blechinger 2016; Bertheau et al. 2017; Mentis et al. 2017; Moksnes et al. 2017). This number can then be triangulated with established statistics on the number of unelectrified people in a country (Moksnes et al. 2017). The use of nighttime illumination data is expected to generate more accurate descriptions of the currently unconnected population than the approach that simply draws a corridor around the existing grid.

ESTIMATING DEMAND

LCEMs tend to deal with issues of demand in three ways, each involving an increasing level of complexity. The first and simplest approach is to simply ignore demand and to drive the model using a pre-determined LCOE or using population density as a proxy for demand (Szabó et al. 2011; Bertheau, Cader, and Blechinger 2016; Bertheau et al. 2017; Moner-Girona et al. 2017). The approach based on a pre-determined LCOE, applied by Szabó et al. (2011), assesses a number of different generation sources with sufficient capacity to plausibly meet access requirements and examines where they might be able to operate at a competitive, pre-determined LCOE. This approach estimates where the grid will be cheapest by simply drawing a corridor around the grid and assuming that everyone within this corridor will be most cheaply connected to the grid. The output of the model is a map indicating where different technologies are competitive (Szabó et al. 2011; see Appendix).

The population density approach allocates technologies by setting requirements for population density and distance from the grid for each technology and then tallying the different technologies used (Bertheau, Cader, and Blechinger 2016; Bertheau et al. 2017). Notably, the population density approach is based, in part, on other modeling work that has sought to estimate the relationship between population density, the distance from the grid, and household demand, including work by Fuso Nerini et al. (2016; see Appendix for details of this work) and Olatomiwa et al. (2015).

The second approach for dealing with demand is to assume a level of demand that is applied to all households or one that distinguishes between rural and urban households. The level can be based on a generic idea of the energy demands from different appliances and estimates of the energy necessary to supply them. A similar approach is to consider energy access goals as laid out by one of the major institutions concerned with this topic—e.g., the IEA level of basic access[13] or a selection of tiers within the World Bank's Multi-Tier Framework for measuring energy access (Bhatia and Angelou 2015; Mentis et al. 2015, 2016; Moksnes et al. 2017; Ohiare 2015; Deichmann et al. 2011; Levin and Thomas 2012; Van Ruijven, Schers, and van Vuuren 2012; Dagnachew et al. 2017; Sahai 2013). One challenge regarding the use of the Multi-Tier Framework is that different publications appear to use different accounts of what levels of consumption fall into which tiers of energy access. Most notably Fuso Nerini et al. (2016) cites the World Bank *Global Tracking Framework*[14] (Angelou et al. 2013, 101), but this differs from the description of energy tiers provided by the World Bank ESMAP report *Beyond Connections* (Bhatia and Angelou 2015, 6). Differences between the two accounts are shown in Table 1. For this report, the *Global Tracking Framework* definition of the energy access tiers is used when controlling for demand across models.

Table 1. Definitions of energy access tiers from two publications

***Beyond Connections* (kWh/hh/yr)**			***Global Tracking Framework* (kWh/hh/yr)**		
	Tier 0	NS		Tier 0	≤ 3
0.012 ≤	Tier 1	< 0.2	3 <	Tier 1	≤ 66
0.2 ≤	Tier 2	< 365	67 <	Tier 2	≤ 321
365 ≤	Tier 3	< 1,241	322 <	Tier 3	≤ 1,318
1,241 ≤	Tier 4	< 2,993	1,319 <	Tier 4	≤ 2,121
2,993 ≤	Tier 5		2,121 <	Tier 5	

Sources: Bhatia and Angelou (2015) and Angelou et al. (2013).
Note: NS = not stated.

The third and final approach is to try to attain detailed estimates of demand by looking at current demand in the country across different income groups and population densities (both of which are thought to correlate positively with demand) and accounting for differences in rural and urban consumption. Models engaging in this level of detail either consider household connections (Moksnes et al. 2017; Dagnachew et al. 2017; Zeyringer et al. 2015; Ellman 2015; Levin and Thomas 2012) or sometimes go further and consider demand from market centers, schools, and health centers in currently unconnected areas, based on government ambition about electrifying these services (Kemausuor et al. 2014;

[13] The IEA level of basic access is assumed to be 500 kWh per household per year for urban households and 250 kWh per household per year for rural households (IEA 2017b).

[14] Fuso Nerini et al. (2016) provides a link that is no longer working. The source is cited as "Source: World Bank Global Tracking Framework, Source: Elaboration of the authors from Ref. [http://documents.worldbank.org/curated/en/2013/05/17765643/global-tracking-frameworkvol-3-3-main-report.]."

Modi et al. 2013; Parshall et al. 2009; Sanoh et al. 2012). Obviously this detailed level of assessment is possible only at smaller scales and contingent upon the data and plans available from the local utility.

As mentioned, it is important to consider demand profiles so that the LCOEs for renewable generation systems are calculated in a way that ensures that the systems can effectively meet household demand (such calculations also require spatially and temporally explicit data on resource availability). Furthermore, incorporating demand profiles is important to ensure that the LCOEs for different generation sources reflect how increasing diversity of demand decreases system costs, thereby driving lower LCOEs for mini-grids and the grid.

Despite the importance of demand profiles, a number of models do not assess the issue in detail, instead estimating LCOEs for different systems based on what are believed to be plausible estimates for different generation systems. This is done either by using average estimates for LCOE for different systems (Levin and Thomas 2012) (which negates the need to assess the way LCOE varies in space based on resource availability) or by using estimates of capital costs ($/kW) that include costs of storage and account for the diversity of demand on the system (Fuso Nerini et al. 2016; Mentis et al. 2015, 2016).

Models that do consider demand profiles adopt a number of approaches. Szabó et al. (2013) assume a standard profile: one-third of demand is anticipated to occur during the day with two-thirds occurring in the evening. Ellman (2015) estimates demand profiles based on an assessment of the appliances in different households and an assumption of when they will be used. Other models use demand profiles established elsewhere in the literature (Bertheau, Cader, and Blechinger 2016; Moner-Girona et al. 2016). Finally, some models add randomness to the demand profiles of each dwelling in an attempt to reflect the fact that different households turn on their appliances at slightly different times (Ellman 2015). Overall, models that more accurately reflect the temporal variability in demand at the level of the household do a better job at accurately allocating the technologies because they can account for the reduced costs that larger systems—such as mini-grids and the grid—can achieve.

ESTIMATING RENEWABLE RESOURCE AVAILABILITY

Resource availability is a central input to LCEMs because the availability of wind, sunshine, and hydro potential is a principal driver of the cost of generating electricity for any distributed renewable system. Models deal with this input in different ways. The simplest models use coarse inputs, breaking the area being modeled into windy and not windy areas or sunny and cloudy areas and determining generating costs from there (Fuso Nerini et al. 2016). More nuanced approaches include the use of historic data, which account for resource availability (Mentis et al. 2017) and allow generation systems to be sized accurately based on a set of reliability parameters, such as ensuring that power outages will not occur on more than 5 percent of days per year (Szabó et al. 2011).

Models that seek to incorporate micro-hydro into their assessments have to contend with a lack of hydrological data in sub-Saharan Africa. They address this by using a mix of topographic data and stream-flow data to identify water bodies that meet minimum requirements for installing micro-hydro facilities (Mentis et al. 2015, 2016; Moksnes et al. 2017; Szabó et al. 2013). Other models (such as Mentis et al. 2017) draw upon work that estimates hydrological potential using similar methods, including ground-truthing through the use of data from river gauges (such as Korkovelos et al. 2018).

ESTIMATING DIESEL COSTS

Models that include the possibility of using diesel generators to provide electricity require a cost of diesel to calculate LCOE. Models either simply assume a price for diesel (usually $1/liter) or use the national diesel price (Sanoh et al. 2012; Modi et al. 2013; Kemausuor et al. 2014; Ohiare 2015; Ellman 2015). The most nuanced approach is to combine national diesel prices with information on transport infrastructure to calculate a spatially explicit diesel price that reflects the cost of transporting diesel to the unconnected area by small truck (Mentis et al. 2015, 2016; Moksnes et al. 2017; Moner-Girona et al. 2017; Szabó et al. 2013).

DETERMINING TARIFFS

Determining the LCOE of grid extension must include some account of the cost of electricity from the grid. This is usually based on the existing electricity tariff (Szabó et al. 2013; Fuso Nerini et al. 2016), though this rate is sometimes amended to use what would be considered cost-reflective tariffs (Parshall et al. 2009). Some models go to the extent of estimating what plausible investments in the grid would do to the tariff price. For example, Modi et al. (2013) considers what would happen if Liberia made investments in its grid, reducing what was extremely expensive grid generation at the time the model was written.[15] A final approach involves linking the outputs of the LCEM to a larger grid optimization model to derive the optimal cost-reflective grid tariff (Moksnes et al. 2017; Mentis

[15] This approach was justified in this instance because Liberia's energy infrastructure was built during the civil war—a period of extreme financial duress—resulting in extremely high grid generation costs that were due to be addressed.

et al. 2015, 2017). Such an approach begins to raise computational challenges for these models and is thus discussed in greater detail below in the section on computational challenges in LCEMs.

DETERMINING INVESTMENT COSTS (CAPITAL AND LABOR)

As mentioned, knowing the investment costs of the different technologies is of central importance to estimating their LCOE. Different LCEMs use different estimates, including institutional estimates such as the World Bank (Mentis et al. 2015, 2016, 2017), consultations with the national utility (Moner-Girona et al. 2016; Modi et al. 2013), or literature reviews (Levin and Thomas 2012; Mentis et al. 2015; Fuso Nerini et al. 2016; Mentis et al. 2017). Because grid investment costs vary in space depending on the terrain where construction is taking place as well as on the distance from any service roads, one model has sought to cost grid infrastructure using a base cost and then increasing that by a factor that reflects the steepness of the terrain model and proximity to the nearest road (Mentis et al. 2017).

Although all models seek to use credible estimates of the cost of grid infrastructure, parameters vary widely across models (see Table 2). Costs vary between contexts, and the larger literature on electricity infrastructure contains a wide range of estimates of these costs. Levin and Thomas (2012) note that grid investment costs described in the literature range from $50,000 to $500,000 per kilometer. The largest variance occurs in the cost of high-voltage power lines (Table 2).

Table 2. Grid investment costs across a selection of LCEMs

Indicator	Fuso Nerini et al. (2016)[a]	Mentis et al. (2015, 2016, 2017)	Modi et al. (2013)	Moksnes et al. (2017)	Sanoh et al. (2012)	Deichmann et al. (2011)	Dagnachew et al. (2017) (low cost)	Dagnachew et al. (2017) (high cost)
Line lifetime (years)	30	30	30	NS	NS	NS	NS	NS
Transformer lifetime (years)	NS	NS	10	NS	10	NS	NS	NS
High-voltage line cost ($/km)[b]	53,000 (108kV), 28,000 (69kV)	53,000 (108kV), 28,000 (69kV)	NS	92,823 (kV not stated)	NS	192,000 (220kV), 90,000 (132kV)	28,000 (132kV)	90,0000 (132kV)
Medium-voltage line cost ($/km)	9,000 (33kV)	9,000 (33Kv)	40,000 (kV not stated)	9,000 (kV not stated)	16,000 (kV not stated)	106,154 (132kV), 23,000 (33kV), 20,000 (11kV)	9,000 (33kV)	23,000 (33kV)
Low-voltage line cost ($/km)	5,000 (0.2kV)	5,000 (0.2kV)	40,000 (kV not stated)	5,000 (kV not stated)	12,000 (kV not stated)	10,611 (kV not stated)	5,000 (kV not stated)	10,600 (kV not stated)
Transformers	$5,000/50kVA	$5,000/50kVA	$105/grid system kW	NS	$1,000	$21,818–$60,000/unit	$5,000/km	$35,000/km
Connection cost for grid ($/hh)	125	125	25	NS	263	NS	100	250
Connection cost for mini-grid ($/hh)	100	100	100	NS	263	NS	100	250
T&D losses (%)	10	7–29[c]	19.2	NS	2	NS	NS	NS
Distribution loss (%)	NS	NS	12		3			
Distribution O&M cost (% installation cost)	2	2	1	NS	NS	NS	NS	NS
Transformer O&M cost (% installation cost)	NS	NS	3	NS	3	NS	NS	NS
Generic grid cost	Szabó et al. (2013) assumes a generic grid construction cost (i.e., for all technologies) of €0.025/kWh/km. Levin and Thomas (2012) assume $200,000/km. Zeyringer et al. (2015) assume $157,470/km. Moner-Girona et al. (2016) assume €40,000/km.							

Notes: NS = not stated. km = kilometer. kV = kilovolt. kVA = kilovolt-amp. kW = kilowatt.

[a] Fuso Nerini et al. (2016) is not a spatially explicit LCEM, and thus its results are not discussed in detail in this review. However, Fuso Nerini et al. (2016) models the dynamics shaping LCEMs, and their outputs are invoked in a number of models reviewed here, so their cost estimates for the grid are relevant for consideration as a driver of variance across LCEMs.

[b] A further challenge in comparing models is the use of different infrastructure requirements for different available voltages.

[c] Range is due to country-specific losses.

Notably, Van Ruijven, Schers, and van Vuuren (2012) sensitivity-test their model to different grid investment costs, ranging from $28,000 to $78,000 per kilometer for high-voltage (HV) lines and $5,000 to $9,000 for medium-voltage (MV) lines (notably smaller than the ranges described in Table 2). They observe that variations in these costs have a larger impact on technology allocation than variations in demand. Dagnachew et al. (2017) likewise tests the sensitivity of their model to high and low capital costs for the grid (see Table 2 for costs). Assuming high costs results in the connection of an additional 20 million to 110 million people to distributed generation, depending on the demand scenario.[16] Finally, Sanoh et al. (2012) similarly finds their model is sensitive to variations in the cost of MV lines.

In addition to using a variety of cost estimates for the grid, models also make different assumptions regarding the capacity of grid infrastructure. In particular, the assumed maximum distance for a low-voltage (LV) power line varies across studies. Mentis et al. (2017) places a boundary on LV power lines at 50 km,[17] Szabó et al. (2011) suggests the limit is 10 km, and Deichmann et al. (2011) suggests it is 120 km. Obviously limiting the extent to which grid connections can be extended has major impacts on which technologies provide the least-cost electrification for which households and individuals.

Distributed generation costs also vary across models (Table 3), particularly in relation to battery life and investment costs for renewable components. Attaining accurate estimates of distributed generation systems is challenging because costs for renewable components are changing rapidly[18] and because different systems are built to different capacities. Battery costs are not easy to represent in a single metric, especially when some models use lead-acid batteries and others use lithium-ion batteries. Different models use different representations of renewable energy cost and capacity, making it difficult to compare costs across models and to interrogate costs in the model publications. Finally, the comparison of costs across distributed systems is complicated by the use of different discount rates in different models. For example, Szabó et al. (2011, 2013) uses 5 percent, Zeyringer et al. (2015) uses 6 percent, and Mentis et al. (2015, 2016, 2017) uses 10 percent.

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[16] The impact is larger at low levels of demand.

[17] Mentis et al. (2017) points out that it is unknown whether this is an optimal length and that the question deservers further investigation. The authors also note that line length is a model parameter that could be changed, though this would have implications for computational intensity.

[18] For a longer discussion, see the section below on computational challenges and time steps.

Table 3. Distributed energy investment costs across a selection of LCEMs

Indicator	Szabó (2013)	Moksnes et al. (2017)	Modi et al. (2013)	Mentis et al. (2015, 2016, 2017)
PV lifetime (years)	NS	NS	20	15–20
Battery lifetime (years)	4	NS	2.5	NS
PV module (stand-alone) capital cost	€1,100/kWp	NS	$1,000/kW	NS
PV system (stand-alone) capital cost	NS	$1,633/kW	NS	$5,500/kW
PV system mini-grid capital cost	NS	$1,363/kW	NS	NS
BOS + installation	€800/kWp	NS	50% of PV price	NS
Battery price	€1.5/Ah	$1,688/kW	$213/kWh	NS
PV O&M	2.5% of PV + battery price	$10/kW	NS	NS

Note: NS = not stated. kWp = kilowatt peak. kW = kilowatt. Ah = amp-hour. kWh = kilowatt-hour. The LCOE for distributed generation involves many more inputs than those shown here, but because many component costs are bundled differently, a comprehensive comparison is not possible. This table is thus intended only to show the variance in price of some of these crucial components.

MODELING THE FUTURE: TIME STEPS

Most LCEMs are concerned with modeling the infrastructure allocations necessary to meet 100 percent access goals at some point in the future. The only exception is Szabó et al. (2011), which seeks to provide an instructive snapshot of where different technologies might be competitive in providing access at the time of publication (2011). Most models of the future consider only a single time step to a single point in the future—these are also known as overnight-build models (Parshall et al. 2009; Sanoh et al. 2012; Mentis et al. 2015, 2016; Moksnes et al. 2017; Van Ruijven, Schers, and van Vuuren 2012). For such models, the point in the future at which access goals are set has implications for the overall investment costs because it affects how discount rates play out (Kemausuor et al. 2014). Only three models use more than a single time step. Modi et al. (2013) considers three time steps in Liberia (at 5, 10, and 15 years in the future). Dagnachew et al. (2017) considers yearly time steps from 2010 to 2030 across sub-Saharan Africa. The IEA states that its model incorporates the process of learning and cost reductions, suggesting that time steps must be used; it offers no details, however, on the number of times these figures are updated (IEA 2017b).

The limited number of time steps has the advantage of limiting the computational intensity of the model, meaning the model is run only once (other computational challenges in the models are discussed in greater detail below). That said, using a single time step does reduce a model's ability to handle dynamic processes such as changing prices (most notably for diesel and renewable components, discussed in greater detail below). Single-time-step models also do not reflect the extent to which grid infrastructure takes longer to build than distributed generation, which has implications in the real world for how long people persist without access to electricity.

Regardless of the number of time steps applied, because the vast majority of models are forward looking, they must include allowances for changes in time-sensitive parameters that are important to electrification costs. These parameters generally include population growth, increasing demand among connected households, changing diesel prices, and decreasing capital costs for renewable components.

POPULATION GROWTH

Models need to account for population growth into the future because increased population results in increased demand. Since population growth is anticipated to be significant in many parts of the world where energy access rates are low, this is a salient driver of demand density and therefore technology choices. Models tend to use population projections from the United Nations (or some other large institution). For models in which demand is differentiated based on whether the demand node is rural or urban, there is a step by which population growth in an area can cause any demand node to change from rural to urban, based on national definitions of rural and urban areas (Kemausuor et al. 2014; Ohiare 2015; Mentis et al. 2015, 2016; Moksnes et al. 2017). Despite accounting for changing demographics in this way, the models reviewed here pay no attention to rural-urban migration dynamics, and the impact of this gap on model findings is not discussed in the modeling literature. However, other authors have pointed out that natural increase, rather than rural-urban migration, is the dominant process driving urban growth in sub-Saharan Africa (Parnell and Walawege 2011), and thus the impacts of this simplification might be limited.

INCREASING DEMAND

Only a few models account for increases in demand. These models seek to account for the fact that newly connected households tend to see their demand increase over time. Modelers usually assess this rise in demand based on data from the utility (Parshall et al. 2009; Sanoh et al. 2012; Modi et al. 2013; Kemausuor et al. 2014) or by using a standard estimate of how demand will increase (Moner-Girona et al. 2016).

FUTURE DIESEL PRICES

Models that consider the capacity of diesel-based systems to meet energy demand have to account for future variations in the cost of fuel. This is a fraught endeavor, with fuel prices being notoriously hard to predict. Consequently, models tend to ignore fluctuations (Sanoh et al. 2012; Modi et al. 2013; Kemausuor et al. 2014; Ohiare 2015) or run multiple scenarios using a high and low cost for diesel (Mentis et al. 2017). It has been suggested that models could source diesel costs by using historical data and smoothing the price over a moving average (Moner-Girona et al. 2016), though no model has implemented this approach.

DECREASING CAPITAL COSTS

A final consideration for models is the issue of declines in the cost of capital infrastructure. This is particularly relevant for renewable components, which have seen steep declines in price in the recent past. Few models address this issue comprehensively, instead using costs at the time of writing. While this approach meets the simplifications of an overnight-build approach—which assumes building infrastructure now that will meet the demand of future populations—it does not capture the very real fact that while infrastructure is being built, the cost of renewable components is expected to fall. This approach not only is likely to underestimate the role for distributed generation substantially (given the substantial price declines that have taken place and that are predicted), but also results in the need to update models with future costs. For example, Mentis et al. (2017) advances the analysis of Fuso Nerini et al. (2016) using updated costs for renewables, and Szabó et al. (2013) updates costs used in Szabó et al. (2011).

Only two models were identified to have accounted for declining renewable costs, based on their multi-time-step approach: Dagnachew et al. (2017), and IEA (2017). Dagnachew et al. (2017) applies a historically derived learning rate to account for the cost declines in renewable technologies.[19] This is applied annually over every time-step in the model (see above) The IEA states that its model fully incorporates the process of learning and cost reductions, considering not only technologies available today, but also those approaching commercialization—though it does not attempt to predict technological breakthroughs (IEA 2017b). Unfortunately, however, the IEA model provides no details on the learning rates, the technologies considered, the eventual prices achieved, or the number of time steps considered. Finally one model (Ohiare 2015) accounts for the potential impact of future cost declines by sensitivity testing their models to significant (250%) reductions in renewable technology costs. Doing so changes the proportion of households that are most cheaply connected via distributed energy in Nigeria from 2% to 35% (Ohiare 2015) (see Appendix).

[19] This learning rate is not published in Dagnachew et al. (2017); rather, it was revealed via personal communication (A. Dagnachew, personal communication, November, 6, 2018). The original derivation of the learning learning rate is published in Stehfest et al. (2014).

COMPUTATIONAL CHALLENGES WITH MODELS

While data challenges (and the variety of ways they are solved) drive part of the variation in model results, the other important source of variability in models is how they deal with dynamic elements of electrification modeling, which require significant computational resources to solve. This section discusses the various ways in which these processes are simplified and addressed.

Computational problems around LCEMs are related to four dominant issues; all of them pertain to the grid, and one also pertains to mini-grids:

- Building the grid network in a way that minimizes total grid length, which is important for minimizing grid cost;
- Capturing the dynamic interaction between LCOE calculations and grid construction decisions;
- Capturing the dynamic interaction between grid demand and grid price, which is an important input for LCOE calculations for the grid; and
- Clustering households when deciding whether to serve them with the grid or mini-grid connections.

THE CHALLENGE OF BUILDING A GRID OF OPTIMAL LENGTH

The challenge of grid length stems from a computational problem commonly known as the traveling salesman problem. In its simplest terms the problem refers to the need to find the shortest route between a set of points.[20] The traveling salesman problem has no "efficient solution,"[21] meaning that the optimal solution cannot be determined definitively at the outset and instead must be generated by iteratively testing a number of different solutions. The challenge is that as the number of nodes for which a shortest route is being sought increases, the number of tests for the solution increases exponentially.[22] Since LCEMs

[20] In the traveling salesman problem, a hypothetical salesperson must travel through a number of cities and, before setting out, needs to define the shortest route connecting all points. An in-depth discussion of this problem is beyond the scope of this paper.

[21] Problems of this sort are also known as NP-complete problems.

[22] The following is a helpful representation of the traveling salesman problem and the computational challenges involved in solving it: https://www.youtube.com/watch?v=SC5CX8drAtU ("Traveling Salesman Problem Visualization," published by poprhythm, August 18, 2013).

typically consider a huge number of demand nodes, resolving this problem accurately entails deploying impossibly large computational resources.

Different models address this challenge in different ways. The simplest approach is to ignore the problem altogether. As already mentioned, some models simply draw a corridor around the existing grid and assume that every household within that corridor will be most cheaply connected to the grid and that anything beyond that will be most cheaply connected with distributed generation (Szabó et al. 2011; Moner-Girona et al. 2016; Bertheau, Cader, and Blechinger 2016; Bertheau et al. 2017).

A second approach, used by Mentis et al. (2015, 2016, 2017), avoids the problem of the traveling salesman by iteratively extending the grid and only connecting those demand nodes that meet certain criteria. Specifically, the approach focuses on cells of demand (rather than settlements) and assesses whether the demand in each cell (which is based on the size of the population and the level of household demand) is sufficiently large to warrant extending the grid (based on the cost of grid extension). The approach does not aim to connect all demand nodes and therefore does not have to determine the shortest path to do so (i.e., the traveling salesman problem). Instead it starts with the cell closest to the existing grid, checks whether it meets the requirements for a connection, and then updates the status of the cell and grid before checking the next cell. This approach accounts for the fact that extending the grid requires strengthening the existing grid (which will incur a cost) by linearly increasing the minimum demand requirement necessary to satisfy the decision to extend the grid. Although Mentis et al. (2015, 2016, 2017) avoid the traveling salesman problem, these studies limit the possibility for grid extension to 50 km from the existing grid, based on what are understood to be technical limitations on MV powerlines[23] (D. Mentis, personal communication, November 8, 2018). In this way the model does not account for the possibilities of extending the backbone of the grid transmission infrastructure.

For models that do include scope for new grid transmission infrastructure and that work by first seeking to connect every demand node to the grid, the approach is to use a simplified heuristic to solve the traveling salesman problem. They use some variation on a minimum spanning tree algorithm, amended to behave in a “greedy fashion” (i.e., first connecting points with the largest demand-to-distance ratio) (Deichmann et al. 2011) and to avoid creating loops (Parshall et al. 2009; Modi et al. 2013; Sanoh et al. 2012; Kemausuor et al. 2014; Ohiare 2015).

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[23] It should be noted that this parameter could simply be changed in the model.

The impacts of these different simplifications are relatively underexplored. The only exception comes from Abdul-Salam and Phimister (2016), who test the approach used in the Network Planner model (Parshall et al. 2009; Modi et al. 2013; Sanoh et al. 2012; Kemausuor et al. 2014; Ohiare 2015), by comparing the heuristic results with the results of a computationally intensive, nonlinear programming formulation that can solve the traveling salesman problem completely. By comparing the two results across 434 simulations of randomly generated nodes, they were able to estimate the accuracy of the heuristic. They found that the nonlinear programming approach outperformed the Network Planner heuristic 85 percent of the time but that the differences were small.[24] They also found that the largest errors occurred when solving for nodes that were highly dispersed (i.e., remote settlements) and that the Network Planner algorithm systematically underestimated the optimal number of grid connections (Abdul-Salam and Phimister 2016).

THE DYNAMIC RELATIONSHIP BETWEEN GRID CONSTRUCTION AND LCOE

Any decision to expand the grid subsequently changes the LCOE for the grid for unconnected demand nodes—because the distance to the grid from those nodes will now have changed. If this change in LCOE is large enough to make render the grid with the lowest LCOE of all the technologies then the grid should be expanded again to connect these nodes, resulting in further changes to the LCOE for the grid for unconnected demand nodes. The only robust means to deal with this dynamic is to run the model iteratively, expanding the grid and calculating the LCOE, until the number of new demand nodes being connected to the grid is zero.

Most models ignore this challenge altogether. As above, models that simply assume a corridor around the existing grid avoid this problem completely (Szabó et al. 2011; Moner-Girona et al. 2016; Bertheau, Cader, and Blechinger 2016; Bertheau et al. 2017). Other models that undertake some sort of grid extension overlook these iterative dynamics, simply calculating the least-cost technology allocation and ignoring the fact that extending the grid will reduce the cost of grid extension for neighboring households (Parshall et al. 2009; Kemausuor et al. 2014; Sanoh et al. 2012; Modi et al. 2013).

Beyond this, two models undertake some sort of iterative approach. As mentioned, Mentis et al. (2015, 2016, 2017) run the model iteratively, assessing adjacent cells and connecting those that meet the requirements for a grid

[24] The average difference was 0.7 percent. The largest difference was 3.7 percent, equivalent to about $1.8 million in grid extension costs, based on cost estimates from Ghana, using input data for more than 1,000 real unconnected settlements.

connection. Though this iterative approach captures the dynamic relationship between grid extent and the cost of subsequent grid connections, it is computationally intensive (D. Mentis, personal communication, February 2, 2018). In the published findings this is managed by limiting the model so that the grid is not extended more than 50 km from the existing and planned grid.

Dagnachew et al. (2017) solves this problem by incorporating 30 time steps into the model. The model assesses the LCOE for each technology (accounting for reduced renewable prices) and recalculates the LCOE for the grid based on the updated extent of the grid from the previous year/time step.

THE DYNAMIC INTERACTION BETWEEN GRID DEMAND AND GRID PRICE

Connecting new households to the grid results in changes to the grid generation price because it both increases overall demand and changes the overall demand profile on the grid. Changes in the price of grid electricity change the LCOE for grid connections; one no longer has an accurate estimate of the cost of connecting households to the grid, so the cost estimate needs to be updated to reflect the reduced grid price. Resolving this problem requires an iterative approach: (1) calculate the LCOE for each technology to determine how many settlements are most cheaply connected to the grid; (2) determine the new grid price (i.e., the tariff) based on this increased demand and altered overall demand profile; and (3) rerun the LCEM to determine how many households are now most cheaply connected to the grid. This process must be repeated until no new grid connections are established.

As with the previous problem, the computational challenges involved in this process are significant because the iteration requires rerunning not only the LCEM but also the grid optimization model to determine the updated grid tariff. Only Mentis et al. (2017) and Moksnes et al. (2017) address this issue to any extent by integrating their LCEMs with the outputs of a grid optimization model (OSeMOSYS). Moksnes et al. (2017), however, undertakes only a single iteration of this process, noting that this likely still results in a grid tariff that is too high. Notably, this single iteration was found to reduce the grid price from $0.125/kWh to $0.08/kWh, with the result that an additional 1.22–1.67 million people would be connected most cheaply by the grid, depending on the demand scenario used (Moksnes et al. 2017). Ignoring or simplifying this issue is likely to underestimate grid connections because both increases in grid extent and increased demand on the grid reduce the subsequent LCOE of grid connections.

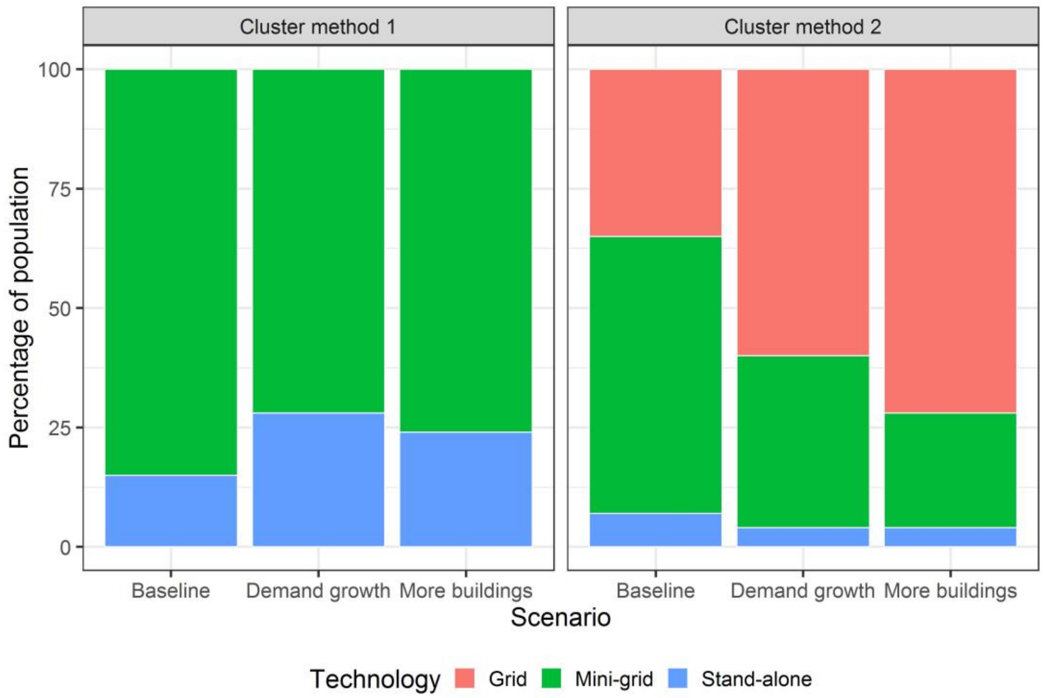
THE CLUSTERING APPROACH USED BY THE MODEL

The issue of clustering is important for determining whether there is sufficient density of demand to warrant the construction of a larger energy delivery system—such as a mini-grid or the grid. In an ideal scenario the model would undertake some assessment of individual households to determine whether the cost savings delivered by the larger system warranted the increased capital expenditure. At some point the model would have to determine which households are suitably close together to warrant clustering and which ones are so far apart that clustering is no longer the cheapest option.

All but one of the models assessed in this review fails to address this problem. Instead, the models simplify things by only considering the cost of connecting an entire settlement (or grid cell, depending on the model) with a single technology. Such a simplification has the advantage of significantly reducing the computational complexity of the model (as a huge number of individual households is reduced to a much smaller number of settlements, or grid cells), thereby vastly reducing the number of calculations necessary and eliminating the need for a clustering algorithm within the model. That said, such a simplification introduces a new problem regarding how one estimates the cost of distribution infrastructure when connecting an entire settlement or grid cell. The models account for this based on the idea of a mean household distance, which is an estimate (either derived or assumed) of the mean distance between households at the demand node (Parshall et al. 2009; Sanoh et al. 2012; Kemausuor et al. 2014; Modi et al. 2013; Ohiare 2015). Based on this number and the number of households in a settlement or cell, the model can generate the total length of distribution infrastructure required and in turn the cost of that infrastructure. To calculate transmission costs, the models tend to assume that transmission infrastructure will need to be built to the center of the cell or settlement.

The only advance on this approach comes from Ellman (2015), which applies the Reference Electrification Model at a small enough scale (Vaishali District, in India) that it can consider every household that was to be electrified. As a result, the model includes an algorithm that determines whether the collective demand from any number of suitably closely situated households warrants constructing a grid or mini-grid connection. Although a detailed discussion of Ellman's (2015) clustering algorithm is beyond the scope of this review, it is worth noting that the model involves a sensitivity test to consider the impact of two different clustering algorithms. The clustering method used drives significant differences in the outcome of the model. Figure 4 shows that under the same scenario the role for the grid is much larger using the second clustering method. The difference in results is driven by the fact that one clustering approach ends up placing households into lots of small clusters that lack the scale to justify a grid connection. The other approach does the opposite, creating large clusters and therefore creating greater opportunities for the scales necessary to make grid connections competitive (Ellman 2015). Since the other models entirely overlook the impacts of a particular clustering dynamic, it is possible that the numbers they produce could be wrong by a similar margin.

Figure 4. The impact of clustering methods on technology allocation across scenarios



Source: This figure is a visualization based on data published in Ellman (2015).

In addition to the four computational challenges described here, LCEMs are simplified representations of reality in two other ways. First, none of them account for the costs of upgrading existing grid infrastructure, a step that would be necessary to ensure that grid connections can supply reliable power to newly connected households. This is generally because the cost-benefit calculus around grid upgrading extends far beyond the imperative to achieve energy access. The only model that offers any sort of exception to this is Ellman (2015), which calculates the cost of unserved need—i.e., it interprets blackouts as costs that are added to the LCOE.[25] Second, LCEMs account only for the capital costs involved in rolling out the necessary infrastructure, completely ignoring the costs

[25] Ellman (2015) does this both to estimate the cost of an unreliable grid and to determine optimal distributed generation capacity, noting that households are often willing to accept lower-cost energy with higher unreliability as long as critical demand is met. See the Appendix for more details.

of capacity building that would be sustain such a huge investment in infrastructure. This is true for both grid and distributed infrastructure.

RESULTS: COMPARING MODEL FINDINGS

It is clear that LCEMs face significant data problems as well as computational challenges, and they solve these problems in a variety of ways. This variation raises the question of accuracy among these models, an issue that is particularly pertinent considering the extent to which these models are intended to aid policy making. One means of exploring model accuracy is to assess the level of agreement across models.

For this analysis, models are compared in terms of the percentage of connections they allocate to distributed-generation technologies. This output from the models is distinct from estimates of financing needs, which are different given that distributed systems tend to cost more than the grid (at the same levels of demand) and which some models have sought to focus on (most notably the IEA). Although financing estimates may be more useful to advocates and policy makers, they are not used here because not all models published these data. Furthermore, findings regarding financing requirements are subject to additional variability based on the fact that different models invoke different capital costs, discount rates, and investment periods. All of these factors also affect technology allocation, but to a lesser extent, and thus technology allocation forms the basis of this comparison.

Comparison across published findings, however, is not straightforward. Models are applied to very different geographies (districts and regions within countries, countries, continents, and the world) and consider different technologies (see Figure 2). They use different parameters, making easy comparison of the results impossible. Many models do not publish their source code, making it impossible to compare models (D. Mentis, personal communication, 10 December, 2018). To address these discrepancies, this analysis includes all published findings of geographies that could be identified in the literature and makes the geographies explicit in the comparison. It identifies the specific model scenarios that are thought to be most comparable based on similar assumptions about demand, which is chosen given its centrality in determining LCOE. This was achieved by considering demand ranging between tiers 2 and 4 of the World Bank Multi-Tier Framework for measuring energy access. It is within this range—around tier 3—that many advocates consider energy access to be plausibly addressed, and all models included some analysis of demand in this range. For both geography and demand, this is an imperfect approach, but it is the best we can achieve based on the published work. Notably, it was not possible to control for factors beyond countries/regions and demand, because no published findings considered both the same geography and the same technology.

The exact scenarios chosen for this analysis can be seen in Table 4. The range of demand in some models is extremely large—for example, Parshall et al. (2011) use a range of 360–2,090 kWh per household per year. Such large ranges are usually based on an assessment of demand that includes urban demand, with the model ascribing a level of demand to settlements based on their size and income. Although the range is large, the model likely uses the low end of the demand range for remote rural settlements, treating them in a manner similar to models that use a single, smaller level of demand. The low end of the demand spectrum ranges from 43.8 kWh per household per year (tier 2) to 360 kWh per household per year (tier 3), suggesting a much more reasonable comparison across models. Overall, the average demand across models (considering the low end of the range for any models invoking a large demand range) is 290.06 kWh per household per year, with a standard deviation of 252.8 kWh per household per year.

Despite efforts to keep demand comparable across models, this approach does not resolve the problem of comparing models based on different parameters. Overall, any cross-model comparison, based on the existing publications, is a fraught endeavor. In consequence, a clear conclusion of this work is that our ability to determine the accuracy of these models is extremely limited. To try to account for the limitations of this analysis, this work has not only undertaken the analysis described above but also tried to make the differences in the models explicit. As a result the analysis includes the following:

1. A description of not only the results deemed comparable across models (red points in Figure 5) but also the scenarios run by the models (blue points in Figure 5), excluding sensitivity testing;
2. Table 4, which makes explicit the scenarios selected for comparison across models along with their levels of demand;
3. A more complete account of all the published model results reviewed in this analysis (Table 5); and
4. A brief narrative of the workings of each set of published model findings (Appendix).

At the outset it is worth noting that LCEMs are complex, and publications documenting their findings frequently fail to include important data on their operation. This report has done everything possible to gain complete clarity on the operation of these models, including writing to many of the authors of publications generating model results. Where they have provided relevant information, this has been included and cited; in cases where information is believed to be missing, this is simply pointed out in the model assessment.

The results of the analysis can be seen in Figure 5. The red points indicate results that are deemed to be driven by levels of demand similar enough to allow for comparison across models. Multiple red points (connected by a bar) indicate that the model ran more than one scenario at a comparable level of demand, and thus there is a range of comparable results. For example, a model might have considered two diesel prices at a constant level of demand. Blue points indicate other results from the model that were not considered suitable for comparison based on their different estimates of demand. The published results are clustered by country or region to allow for comparison where possible. This analysis considers only published results that provided an estimate of the *newly connected population*, according to the least-cost technology allocation. Models that only provided results for the distribution of technologies across the whole population once universal electrification had been achieved were ignored (this is because such models would generate much larger estimates for grid connection as they would include all the people already connected to the grid).

Figure 5. Comparison results across LCEMs estimating technology allocation for universal electricity access

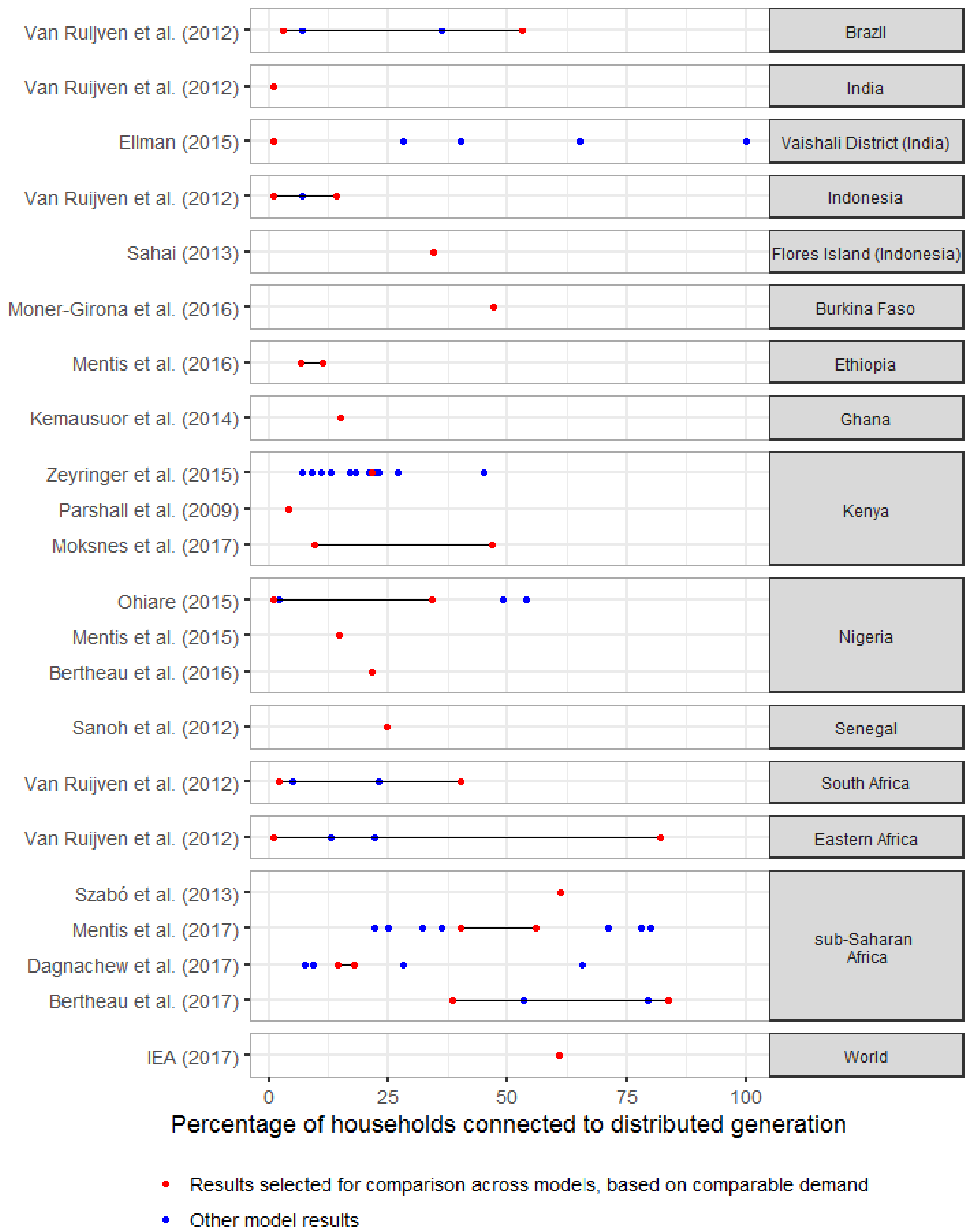


Table 4. Details of scenario selection for comparison across models and publications (supporting information for Figure 5)

Study	Demand, kWh (tier)	Notes and additional/selected scenarios
Parshall et al. (2009)	360 (2) – 2,090 (4)	NA
Sanoh et al. (2012)	73 (2) – 1,398 (4)	NA
Kemausuor et al. (2014)	150 (2), 4% growth	NA
Ohiare (2015)	400 (3)	Declining solar costs
Mentis et al. (2015)	850 (3) – 1,750 (4)	NA
Mentis et al. (2016)	250 (2) – 1,500 (4)	50 (2) – 1,700 (4)
Mentis et al. (2017)	695 (3)	High and low diesel price
IEA (2017)	250 (2) – 500 (3), increasing over time to reach national averages	NA
Moksnes et al. (2017)	43.8 (2) – 423 (3)	423.4 (3) – 598 (3)
Szabó et al. (2013)	250 (2) – 1,000 (4) [a]	NA
Moner-Girona et al. (2016)	40 (1), 4% growth	NA
Van Ruijven et al. (2012)	420 (3)	High demand; high and low investment costs; high and low generation costs; PV only (mini-grids do not consider whether population densities can support them)
Dagnachew et al. (2017)	75 (2) – unspecified (3)	322 (3)
Bertheau et al. (2016)	NA	Existing grid and pop density, planned grid and grid corridor
Sahai (2013)	NS	NA
Ellman (2015)	NS	Only selected reliable grid scenario; assumed in all other models
Zeyringer et al. (2015)	164 (2) – 1,880 (4)	NA

Note: NS = not stated; NA = Not Applicable

[a] This range is based on the use of 4–15 kW diesel generators, which produce 35–135 MWh per year, which would provide 30–140 households with tier 2–4 electricity access (M. Moner-Girona, personal communication, January 15, 2019).

From the results selected for comparison (red points), it is clear that results vary widely, both across models and within regions and countries. Across models of different regions and countries, the percentage of the population most cheaply connected by distributed technologies ranges from close to 1 percent to 82 percent. While such large variation might be expected across regions and countries, ranges are also large within regions and countries with more than one published model result. Results range from 4 percent to 47 percent in Kenya, from 1 percent to 34 percent in Nigeria, and from 18 percent to 79 percent in sub-Saharan Africa. Even within models considering a single geography, the range can be large across what seem to be plausible demand scenarios. Van Ruijven et al. (2012), considering East Africa, shows that distributed technology allocations are cheapest for anywhere between 1 and 82 percent of the population. Further, considering the variety of results within each model (blue points for each single model), it is clear that varying inputs across models makes a huge difference in terms of technology allocation.

Regarding the split between grid and distributed technologies, it is also notable that the individual countries modeled here do not appear to represent the contexts apparent across the larger regions of which they are a part. For example, published findings on Burkina Faso, Ethiopia, Ghana, Kenya, Nigeria, Senegal, and South Africa all suggest that, at most, less than 50 percent of new connections would come from distributed technologies, while for the sub-Saharan African region just under half the comparable results (three out of seven) predict that more than 50 percent of the population would be most cheaply connected by distributed technologies. This is not an impossible outcome; these countries constitute only about 30 percent of the currently unelectrified population in the region (IEA 2017a). If the models are accurate, however, these countries are not representative of the larger region. Notably, these countries include the countries that Trotter, McManus, and Maconachie (2017) identify as dominating the literature on electrification modeling, leaving out only Tanzania.[26]

In addition to variation regarding the split between grid and distributed technologies, the split within distributed technologies (i.e., between mini-grids and stand-alone systems) again reveals slightly confounding results (Figure 6). Individual countries modeled here—such as Burkina Faso, Ethiopia, Flores Island, Nigeria, and to a lesser extent Ghana—indicate a larger role for mini-grids. The exception is Senegal, where stand-alone systems dominate. Despite this, across the sub-Saharan African region there is remarkable agreement that stand-alone systems will dominate. Complicating matters, this trend toward stand-alone systems breaks down at the level of the world, where the single global model suggests a larger role for mini-grids. This last finding is especially confounding because the IEA model for the world is based on the OnSSET model used by Mentis et al. (2017), which points to a larger role for stand-alone systems in sub-Saharan Africa. The difference might be explained by the IEA models' inclusion of developing Asia, where higher population densities could drive a larger role for mini-grids.[27] In that case, however, it is surprising that the IEA model does not indicate a greater role for the grid, unless this is undermined by the low demand used in the IEA model (rural household demand is 250 kWh per year), though the model does indicate that it increases demand over time to reach the national average. The other potential explanation is that, like the published findings from the OnSSET model, the IEA model limits grid extension to 50 km from existing grid infrastructure. Otherwise the explanation could be in

[26] The countries that dominate the literature on electrification modeling are Ethiopia, Ghana, Kenya, Nigeria, South Africa, and Tanzania.

[27] It is also possible that higher demand in developing Asia could drive more mini-grid connections; however, the IEA model assumes demand of 250 kWh per rural household and 500 kWh per urban household, so that is not the case in this model.

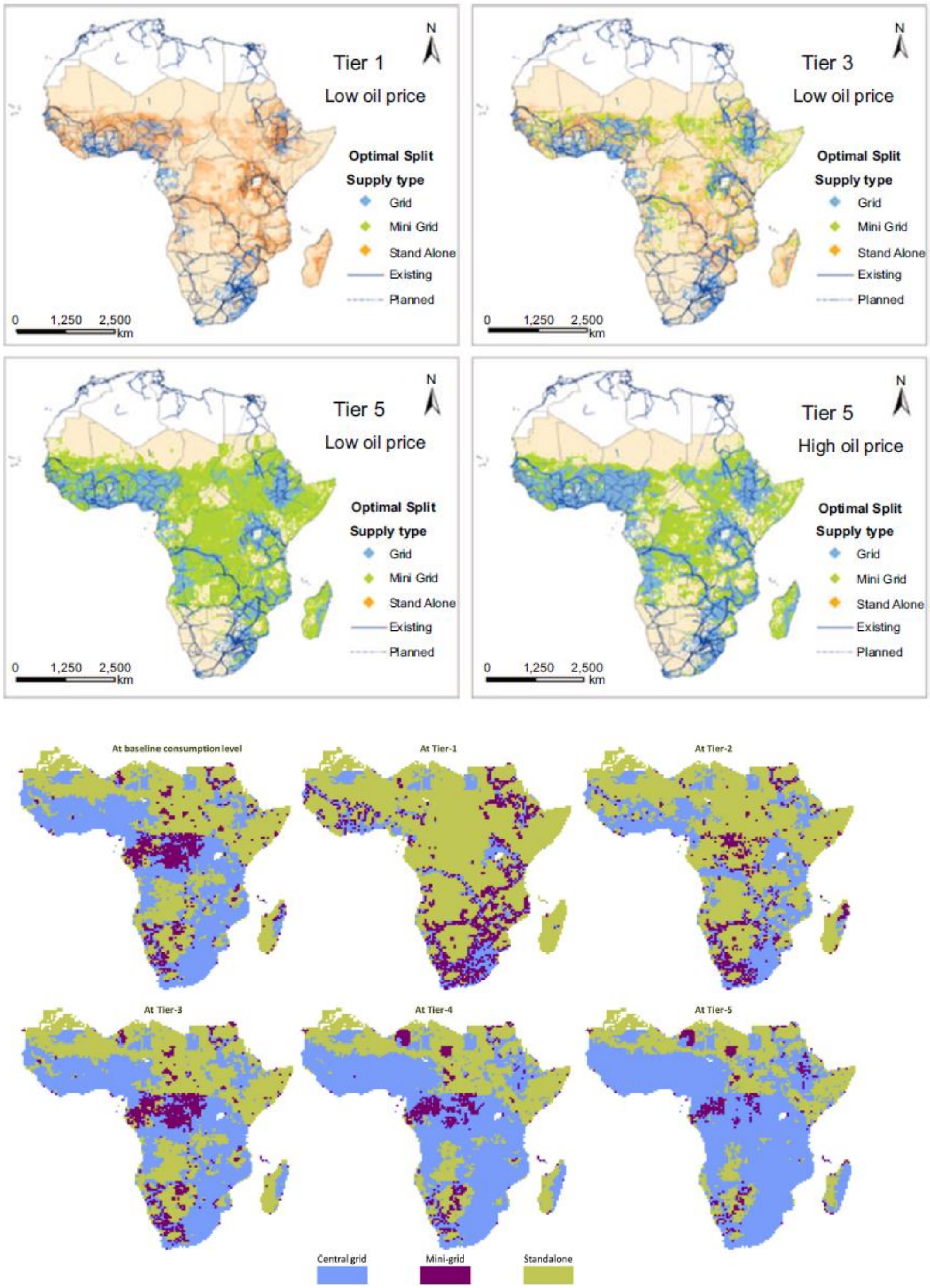
the use of learning rates within the IEA model. Unfortunately, none of this can be explored owing to a lack of data on the operation of this model.

Figure 6. Variability of mini-grid and stand-alone technologies as a proportion of distributed technologies

While the above explanations may plausibly explain the different allocation of mini-grids versus stand-alone systems across models and geographies, it is likely that the sample here is too small to allow for effective comparison—especially when one considers the variation in grid versus distributed connections mentioned above. Supporting this conclusion is the fact that for some countries, the same model running slightly different scenarios suggests vastly different roles for mini-grids compared with stand-alone systems. This is most apparent in the case of Kenya, where Moksnes et al. (2017) shows large differences based on demand (ranging from about 43 kWh per household per year (low demand) in rural areas to about 400 kWh per household per year (high demand) (see Table 5). Likewise, as mentioned, Ellman (2015) shows large differences in the choice of distributed technologies in Vaishali District, based on the clustering algorithm used in the model.

While the variation across models and geographies appears real, and while the split among models between stand-alone and mini-grid systems suggests confounding results, some commonalities do seem to appear across models. Even though there is disagreement on the proportion of people who are connected most cheaply using distributed generation technologies, there is agreement that for the vast majority of geographic space, distributed technologies will be the cheapest option (see Figure 7). Although this might seem like a paradox at first, it is a result of the fact that most areas have relatively low population densities and that, in a number of contexts, population densities are highest in relatively close proximity to existing grid infrastructure. Agreement on this matter is useful for planning because it means that while caution might need to be exercised in terms of what investments to make overall, one can allocate certain technology options to certain jurisdictions with much greater certainty.

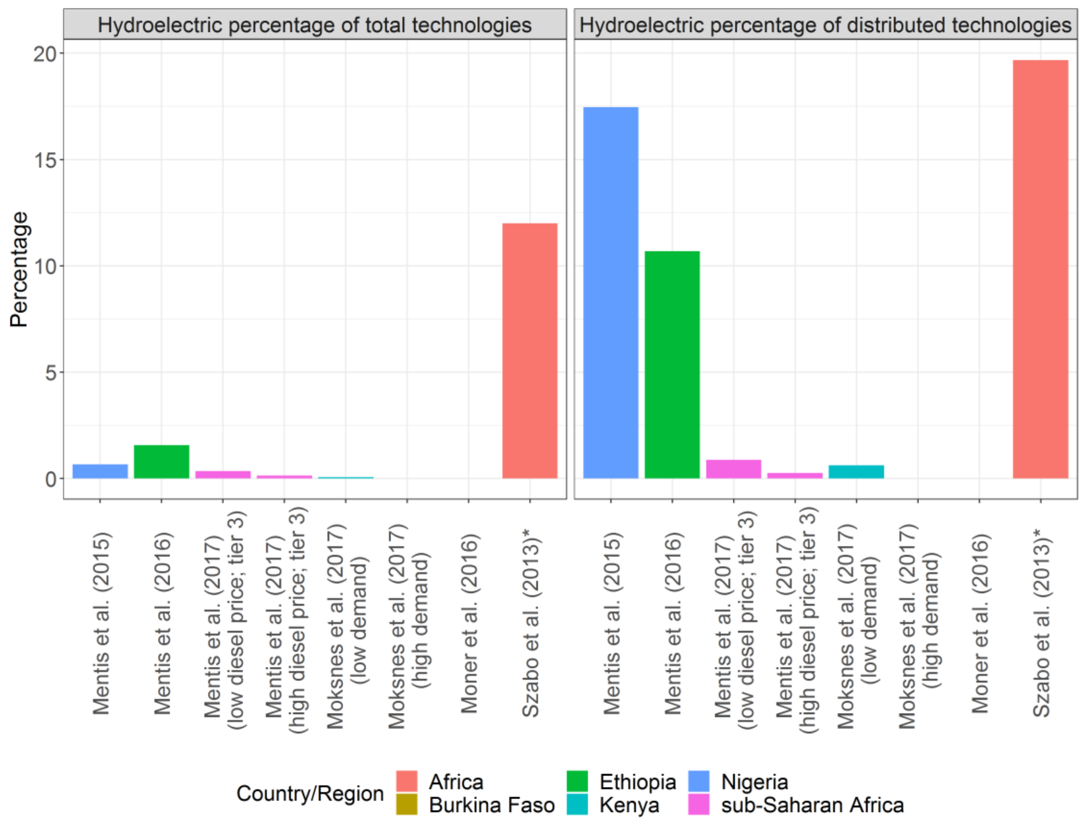
Figure 7. Spatial distribution of least-cost technologies in sub-Saharan Africa according to two models, by level of demand and oil price



Sources: Mentis et al. (2017) - originally produced by the Joint Research Centre of the European Commissions - (top) and Dagnachew et al. (2017) (bottom).

Finally, there appears to be emergent agreement across models that micro-hydro will have only a limited role in the process of electrification, even though it has a relatively low LCOE for generating energy (Fuso Nerini et al. 2016) and significant generation potential from micro-hydro has been identified across sub-Saharan Africa (Korkovelos et al. 2018). As Figure 8 shows, among LCEMs that consider hydroelectric mini-grids, they are the cheapest option for less than 12.5 percent of the population, with most models indicating a role of less than 2.5 percent. As a relative share of distributed technologies, mini-hydro connects less than 20 percent of the population. This conclusion, however, comes with the caveat that efforts to identify and cite potential for small-scale hydroelectric generation face persistent data problems (Korkovelos et al. 2018).

Figure 8. Role of hydroelectric technologies in energy access



Note: Dagnachew et al. (2017) test for hydroelectric but do not publish specific findings.
* This refers to all households, not simply the newly connected ones. However, since any number of mini-hydro connections will likely be new, this is thought to be a comparable result.

Table 5. Summary of models

Study	Model/institution	Country	Population data	Data source for location of existing grid	Technologies assessed	Locate electrified population	Demand assessment	Demand (kWh/hh/yr)[a]
Parshall et al. (2009)	Network Planner/ Columbia University	Kenya	Grid (~10 km^2–15 km^2)	Local utility	Grid, mini-grid (diesel), stand-alone (PV)	Local utility	Derived across income, includes institutions, increasing over time	350–2,090
Sanoh et al. (2012)	Network Planner/ Columbia University	Senegal	Settlements (low res)	Local utility	Grid, mini-grid (diesel), stand-alone (PV)	Local utility, census, etc.	Derived across income, includes institutions, increasing over time	93–1,498
Modi et al. (2013)[b]	Network Planner/ Columbia University	Liberia	Settlements (high res)	Local utility	Grid, mini-grid (diesel), stand-alone (PV)	Local utility, census, etc.	Derived across income, includes institutions, increasing over time	300–2,400
Keumasor et al. (2014)	Network Planner/ Columbia University	Ghana	Settlements (low res)	NS[c]	Grid, mini-grid (diesel), stand-alone (PV)	Ministry of Energy	Derived across income, includes institutions, increasing over time	169.5; increasing based on settlement size and income
Ohaire (2015)	Network Planner/ Columbia University	Nigeria	Settlements (low res)	NS	Grid, mini-grid (diesel), stand-alone (PV)	NS	Assumed, ignores institutions	330 and 400
Mentis et al. (2015)	OnSSET/KTH	Nigeria	Grid (6.25 km^2)	AfDB (2011)	Grid, mini-grid (PV, wind, diesel, hydro), stand-alone (PV)	Grid corridor, electrification rate	Assumed, derived, ignores institutions	850 (rural)–1750 (urban)
Mentis et al. (2016)	OnSSET/KTH	Ethiopia	Grid (6.25 km^2)	AfDB (2011)	Grid; mini-grid (PV, wind, diesel, hydro), stand-alone (PV)	Grid corridor, electrification rate	Assumed, derived, ignores institutions	750 (rural)–1500 (urban)
Mentis et al. (2017)	OnSSET/KTH	Sub-Saharan Africa	Grid (1 km^2)	AfDB (2011), OpenStreetMap	Grid, mini-grid (PV, wind, diesel, hydro), stand-alone (PV)	Nighttime illumination, population data, transmission grid, road network	Assumed, ignores institutions	All energy access tiers
IEA (2017)	Based on OnSSET	Global	Grid (1 km^2)	NS	NS	NS	Assumed, ignores institutions	250 (rural)–500 (urban); increasing over time to reach the national average
Moksnes (2017)	OnSSET/KTH	Kenya	Grid (1km^2)	AfDB (2011), OpenStreetMap	Grid, mini-grid (PV, wind, diesel, hydro), stand-alone (PV)	Nighttime illumination, grid, roads, electrification data	Derived, ignores institutions	Low scenario: 43.8 (rural)–423 (urban); high scenario: 423 (rural)–598.6 (urban)
Szabó et al. (2011)[d]	ECJRC/RE2nAF	Africa	Grid (1km^2)[e]	Variety of sources	Grid, mini-grid (diesel, PV)	Electrification rate[e]	Assumed	250 kWh–1,000 kWh (derived tier 2 and tier 4)[f]
Szabó et al. (2013)	ECJRC/RE2nAF	Africa	Grid (1 km^2)	Variety of sources	Grid; mini-grid (diesel, PV, hydro), stand-alone (PV)	NA	Assumed	250 kWh–1,000 kWh (derived tier 2 and tier 4)[f]
Moner-Girona et al. (2016)	ECJRC/RE2nAF	Burkina Faso	Settlements	Burkina Faso Utility	Grid; mini-grid (PV, hydro, diesel), stand-alone (PV)	Rural electrification agency	Derived, includes institutions	200; increasing by 4%/yr

Study	Model/institution	Country	Population data	Data source for location of existing grid	Technologies assessed	Locate electrified population	Demand assessment	Demand (kWh/hh/yr)[a]
Deichmann et al. (2011)[g]	World Bank	Ghana, Ethiopia, Kenya	Settlements	NA	Grid, mini-grid (PV, wind, diesel, PV-wind, biodiesel), stand-alone (PV, wind, diesel)	NA	Assumed	1,440
Levin and Thomas (2012)[g]	NA	150 countries	Settlement (high res) and grid (0.25° × 0.25°)	NA	Grid, mini-grid	NA	Assumed and derived	50–10,000
Van Ruijven, Schers, and van Vuuren (2012)	NA/PBL-Utrecht	Brazil, India, Indonesia, South Africa, Eastern Africa	Grid (0.5° × 0.5°)	OpenStreetMap	Grid, mini-grid (wind, diesel), stand-alone (PV)	Grid corridor, electrification rate	Assumed	65 - 420
Dagnachew et al. (2017)	NA/PBL-Utrecht	Sub-Saharan Africa	Grid (0.5° × 0.5°)	OpenStreetMap	Grid; mini-grid (PV, diesel, wind, hydro, hybrid), stand-alone (diesel, PV)	Grid corridor, electrification rate	Derived and assumed scenarios	Derived: tier 3–tier 4; assumed: all energy access tiers
Bertheau, Cader, and Blechinger (2016)	Reiner Lemoine Institut/Berlin	Nigeria	Census data, polling data, schools data	NA	Grid, mini-grid, stand-alone	Nighttime illumination and data on infrastructure (schools) electrification status	NA	NA
Bertheau, Cader, and Blechinger (2017)	Reiner Lemoine Institut/Berlin	Sub-Saharan Africa	Settlements	AfDB, UN DESA and country ministries and agencies	Grid, mini-grid, stand-alone	Nighttime illumination and electrification rate	NA	NA
Sahai (2013)	NA	Flores Island, Indonesia	Settlement	Local utility	Grid, mini-grid (PV), stand-alone (PV)	Derived from census	Assumed (minimum defined by Indonesia power utility)	Met by 350Wp SHS
Zeyringer et al. (2015)	NA	Kenya	Grid (500 km × 500 km)	OpenStreetMap	Grid, stand-alone (PV)	Grid corridor, electrification rate	Derived	164–1,880
Ellman (2015)	Referene Electrification Model/MIT	Vaishali District, India	Arial photos and learning algorithm	Local utility	Grid, mini-grid (PV, diesel), stand-alone (PV, diesel)	Grid corridor, electrification rate	Derived	~220–400

Notes: NS = not stated; NA = Not Applicable

[a] Assuming 5 people per household where demand is stated per capita.

[b] Not included in Figure 5 as they did not calculate the LCEM for 100 percent access.

[c] Not stated in the published workings of the model.

[d] Not included in Figure 5 as they did not provide explicit results comparing grid versus distributed generation.

[e] Personal communication, Moner-Girona, January 15, 2019.

[f] Based on the use of a 4–15 kW diesel generator, which can produce a maximum of 35 MWh to 130 MWh a year. It would give 30–140 households electricity at tier 2–4 (personal communication, Moner-Girona, January 15, 2019).

[g] Not included in Figure 5 as they calculate the grid from scratch, ignoring any existing grid network.

CONCLUSION

Based on the analysis presented here, it is clear that capacity to compare findings across models is limited and thus so is our capacity to interrogate the accuracy of these models. Furthermore, to the extent that we can make comparisons across models, there is significant variability both across models and across geographies. Given the sources of variance across LCEMs, there is valuable work to be done by modelers to quantify the sources of variability across models and develop better uniform proxies and computational logics, so as to generate more accurate, and therefore useful, models to support policy makers and advocates.

The limited capacity to determine the accuracy of different models, as well as the variance in the model findings, suggests that policy makers and advocates should exercise caution when invoking model findings to advocate for specific investment targets around different technologies. While models are expected to be more accurate at the country level—owing to the availability of better-quality data—advocates using such models would be well advised to seek out the published results from multiple models or to consider multiple scenarios. For regional or global cases, they should exercise even greater caution considering the lower-quality data inputs and limited scope for triangulation. Given the variation across countries, any advocacy built around the findings from these regional or global models needs to pay close attention to the countries that constitute any finance or infrastructure portfolio to make sure they reflect the countries for which model results are published. In all cases advocates and policy makers should lean toward using models that publish their inputs and computational logic. This last recommendation speaks to a specific weakness of the IEA (2017) model, which is heavily cited despite publishing extremely limited information about its inputs.

When considering the results of LCEMs and their implications for financing and infrastructure planning, it is important to remember that such models address only the cost of increasing capacity to achieve access. They ignore the costs of upgrading the grid for reliability and expanding capacity for industrial demand. These actions, while not necessarily a priority for increasing access, are central to achieving reliable industrial supply and integrating renewables onto the grid.

With these caveats in mind, policy makers should seek to take advantage of the apparent spatial agreement among the models. This information can be useful for creating effective concessions in which distributed technologies are expected to be the cheapest technology because the small unit costs can be bundled to make them attractive to contractors. Further, such spatial specificity means that policy makers can assure private operators that in certain areas the grid will not be rolled out and thus grid arrival will not threaten private generation efforts.[28] Both of these elements are real advantages of the current models.

Finally, there are multiple actions that modelers could take to improve the quality of models or to advance our understanding of the sources and scale of variance across models. These include the following:

1. Seek to improve the quality of the crucial data inputs in the models by focusing on
    a. Improved data on the geolocation of the existing grid, and
    b. Improved and standardized data on the capital costs of grid infrastructure and fuel costs.
2. Sensitivity-test models using different inputs on existing grid extent—for example, comparing OSM and AfDB maps.
3. Sensitivity-test models to different computational logics, comparing the use of population density (raster data) with settlements (point data).
4. Research effective means for integrating clustering algorithms into LCEMs, and sensitivity-test the models to the use of different clustering algorithms.
5. Test the accuracy of different grid expansion approaches, comparing, for example, the approach used in the Network Planner models and the use of a grid corridor.
6. Explore opportunities to take advantage of cheap, remote computing resources to test the implications of adopting an iterative approach to grid extension and/or LCEM integration with grid optimization models.
7. Increase the number of models using multiple time steps, and explore the impacts of using such time steps on the capital costs of renewable energy components.
8. Include scenarios in models that allow for comparison across models (regardless of the specific inputs being used in the model) so that model variability can be assessed. Suggested values would be a fuel price of $1 per liter and a tier 3 level of demand.
9. Adopt a standard means of describing the parameters for assessing distributed energy generation so that any reader can assess the degree to which costs used are realistic or not.

[28] Although this approach clearly acknowledges a role for private actors in supplying electricity generation infrastructure, this report is not endorsing a simple private model of energy provision. Rather, it recognizes that there are expected to be increased possibilities for the private sector, although the exact relationship between the private and public sectors in supplying such generation is beyond the scope of this work.

APPENDIX: MODEL DESCRIPTIONS

This appendix provides a brief description of each of the published results reviewed as part of this report. The narrative reviews are not systematic and are intended only as greater context for each of the publications reviewed. It is impossible to include the full workings of every model in this summary, and thus the reader is directed to the original publication for greater details. During this process of summary, it is possible that small errors have been introduced in the description of each model. If this is the case and the reader identifies an error, please contact Oxfam at the address provided within the foreword of this report.

The publications are discussed in the order that they appear in Table 5, which clusters publications by the model they use, allowing for a more effective narrative account across the publications.

Two of the models have been applied to a number of contexts (see Table 5): the Network Planner model (Ghana, Kenya, Liberia, Nigeria, and Senegal) and the OnSSET model (Ethiopia, Kenya, Nigeria, sub-Saharan Africa, and global). Thus it is valuable to briefly discuss the logic of these two models. This appendix proceeds by describing each model in general terms and then identifying the publications that used this model.

The **Network Planner** model comes out of the Department of Mechanical Engineering and the Earth Institute at Columbia University. The model uses actual electrification data from the utility as well as specific data on the location of existing grid infrastructure gleaned from different sources depending on the context being modeled.

The Network Planner model begins by creating a demand map—a geographically explicit map of unmet demand for the geography being considered. This map is based on the aggregation of households into known settlements, which are then defined as a single point of demand. Next the model estimates the costs of meeting demand in every settlement based on the different distributed technologies being assessed (stand-alone PV, stand-alone diesel, diesel mini-grids, grid) by calculating the LCOE for each source. For stand-alone systems, this is simply the cost of suitably sized generation equipment divided by the demand that will be met by that equipment. For mini-grid technologies, the model has to account for the distribution equipment necessary to carry electricity from the point of generation to households. This is estimated from a parameter called the mean household distance, which describes the average distance between households in a settlement, and therefore the total distribution costs involved in connecting the settlement either to the grid or a mini-grid.

The model computes the cost of grid electrification in two parts. First it calculates what it calls internal costs, which are non-transmission costs. These include the costs of equipment such as transformers, distribution costs (calculated the same way as for mini-grids), and generation costs. The internal costs of generation are then compared with the cheapest distributed generation option. If the distributed option is cheapest, then it is selected for the settlement. If, however, the internal cost of grid electrification is less than the cost of the distributed option, the second part of the grid cost—known as the external cost—is calculated. The external cost is the cost of connecting the settlement to the existing grid. This is calculated based on an estimate of the cost of extending the grid—represented in cost per kilometer—multiplied by the distance between the settlement and the existing grid. The external cost is then compared with the difference in cost between the cheapest distributed generation technology and the internal grid cost. If the external grid cost is less than the difference, the settlement is identified as grid connected. If the external cost of the grid is greater than the difference, then the distributed technology has the lowest LCOE for the settlement.

The Network Planner is an established and elegant model for selecting the least-cost electrification technology. That said, it suffers from the fact that it ignores the most remote and isolated populations that do not get registered in population data sets that geolocate existing settlements. Such populations would almost certainly be connected most cheaply by stand-alone systems. Furthermore, the model is sensitive to the mean household distance parameter, which is often untested. A test of the model's network expansion heuristic shows that while being suitably accurate it does tend to slightly underallocate grid connections, especially among remote, isolated settlements (Abdul-Salam and Phimister 2016). Finally, the Network Planner model fails to account for the fact that once the grid has been built (i.e., if a settlement is grid connected), this changes the cost of connecting other settlements to the grid because the grid has now moved. It also fails to account for the manner in which increased demand on the grid is likely to reduce generating costs.

Parshall et al. (2009) applies the Network Planner model to Kenya. The model compares grid connections with diesel mini-grids and stand-alone PV (with a diesel generator at the market center to support productive loads).[29] Because high-resolution settlement data were not available in the country, the model is resolved to the level of the "sublocation," which typically represents populations of 5,000–15,000 people in an area smaller than 15 km^2. The model includes

[29] Parshall et al. ignore hydro and wind because, at the time of writing, these potentials were not well understood.

schools and clinics that are known to exist in the sublocations and considers the grid extent in Kenya as of 2007.

The authors use the model to estimate demand based on four categories, determined by the size of the population in a sublocation as well as average income. According to their calculations, demand ranges from a low of 310 kWh per household per year for domestic use and 50 kWh per household per year for productive use to a high of 1,750 kWh per household per year for domestic use and 360 kWh per household per year for productive use. Institutional demand ranges from 360 kWh per year for a small clinic to 15,000 kWh per year for a large boarding school.[30] The model runs over a 10-year period and accounts for population growth.

The model could not use population data to calculate grid costs because the data were not available at a suitably high resolution. Instead, the model builds infrastructure either to a known market center or to the middle of the sublocation. A further condition (applied to account for the fact that people are not evenly distributed across a sublocation but rather are organized in small clusters) was that households would be equally spaced over 20 percent of the sublocation. Furthermore, it was required that for any sublocation, 50 percent of the population had to be located within 300 meters of a transformer. This allowed the model to calculate the number of transformers necessary to connect the population of a sublocation to the grid or mini-grid. The model was further ground-truthed to make sure it delivered sensible results at a small scale.

The model compares two electrification targets, both for 10 years in the future: (1) “realistic target” - 65 percent of the population connected in urban areas with 30 percent connected elsewhere; and (2) “universal access” - 100 percent access. Under the realistic access scenario, the model connected 5,565 (out of the total 6,737) demand nodes to the grid. This translated into 41 percent of households being electrified most cheaply by the grid. For the universal access scenario, the model put 96 percent of households on the grid (6,002 demand nodes). The high proportion of grid-connected households is thought to be a result of Kenya’s current population distribution: 50 percent of Kenyans reside in 3 percent of the country’s land and live at densities of more than 500 people per km^2. More than 90 percent of the country’s population lives at population densities greater than 125 people/km^2.

[30] Estimates were based on assessments of what demand in these centers looks like.

Table A1. Results from Parshall et al. (2009)

Scenario	% of households served by:		
	Grid	Mini-grid	Stand-alone PV
Realistic access	41	Not stated	Not stated
Universal access	96	Not stated	Not stated

Sanoh et al. (2012) applies the Network Planner tool to Senegal. The model is applied on top of a set of concessions into which the country has been divided as part of an effort to privatize electrification. Each concession includes 5,000–10,000 customers, with the electrification status of different populations determined from a mix of sources, including the utility and the census. The model compares grid extension with diesel generators and solar PV, considering electrification targets over a 10-year period. It estimates demand from data detailing patterns of electricity use. The result is demand that varies based on the population size of any concession, from 73 kWh per year to 1,398 kWh per year for households, and from 223 kWh per year (clinic in small settlement) to 1,478 kWh per year (school in large settlement) for institutions. Productive use ranges from 20 kWh per household per year in small settlements to 100 kWh per household per year in large settlements. The model accounts for future growth based on population growth (affecting both future domestic and institutional demand) and increasing productive use. The focus on increased productive demand is derived from historical assessments of Senegal showing that businesses have tended to connect to electricity when it has been made available.

The model assumes that all urban areas (> 5,000 people) are electrified by the grid, and therefore all urban electrification is allocated to the grid through infilling with low-voltage lines. Overall the model produces a technology allocation in which 75 percent of households are connected to the grid, 18 percent are connected to stand-alone PV, and 7 percent are connected to diesel mini-grids.

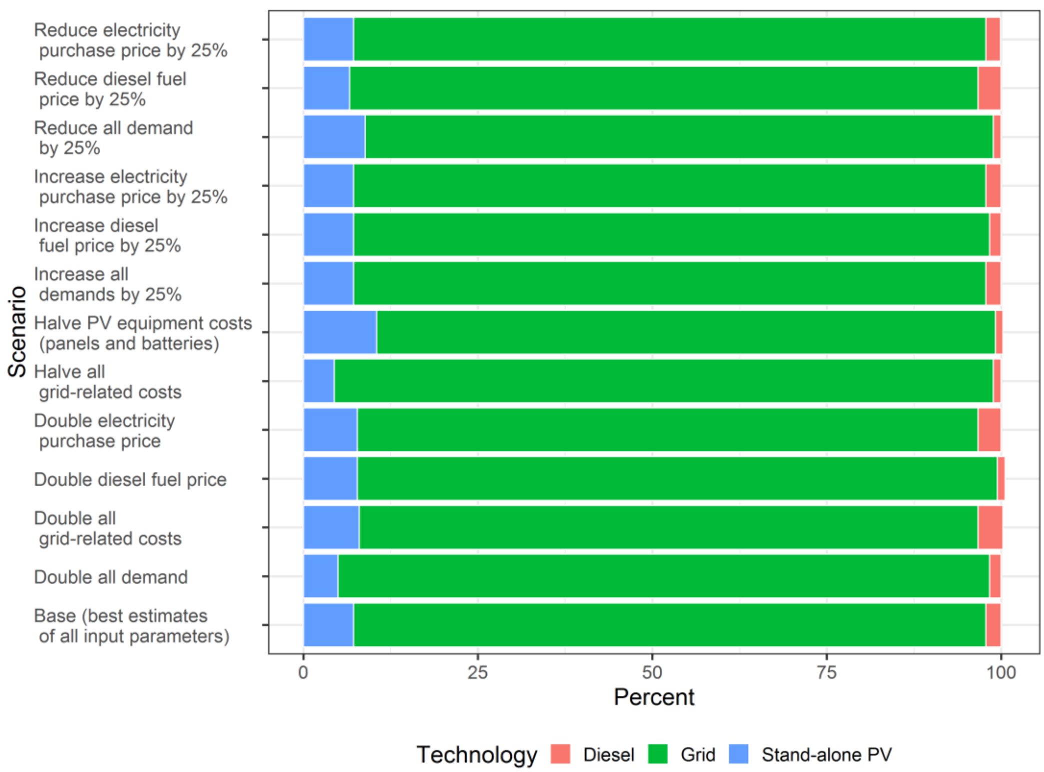
Table A2. Results from Sanoh et al. (2012)

Indicator	Grid	Diesel mini-grid	Stand-alone PV
Number of additional households connected	422,448	37,170	102,206
% of additional households connected	75.20	6.62	18.19

Source: Derived from Sanoh et al. (2012) by adding 288,000 urban households that get connected to the grid (referenced on page 21) to the number of rural households connected to the grid (contained in Table 7).

The model is notable for, again, allocating a large percentage of the population to the grid. Notably, this proportion falls if the model considers only rural electrification. In that case 49 percent of households are connected to the grid, 14 percent are connected to diesel mini-grids, and 37 percent are connected to stand-alone technologies. In the most sparsely populated regions, the grid is the cheapest means to connect only about 24 percent of the population. Such numbers show the large spatial variability of the least-cost technology. The study also highlights the differences in the per capita cost of connection across rural and urban areas and across technologies: the per capita cost of the urban grid is $409; the rural grid, $1,048; rural diesel, $850; and rural PV, $723. Sensitivity analysis on this study shows that the greatest scope for reducing cost comes from halving the price of grid connections; it also shows sensitivity to PV prices, though this is largely confined to rural areas (Figure A1). Overall, the sensitivity analysis shows the prominence of the grid across all cases examined, though this prominence is a result of the number of urban connections.

Figure A1. Results of sensitivity analysis from Sanoh et al. (2012)



Source: This visualization is derived from Sanoh et al. (2012). These results were unpublished but are compiled from published material.

Modi et al. (2013) models the Liberian energy sector using the Network Planner tool. The model does not use an overnight-build approach but instead considers three phases (a 5-year period, a 10-year period, and a final 15-year period) to 2030. The aim of the model is to achieve 100 percent electricity access in urban areas and 70 percent access in rural areas.[31] In Liberia the model was built on top of an excellent set of census data that covered the model needs for each settlement—geolocated point data on each settlement, along with information on settlement size. The model incorporates energy demand from schools and health centers but does not include market centers or public usage (street lights, government offices, police stations, etc.). The model does not account for connecting sites of planned mineral extraction to the grid—data for such sites were not available—even though the authors believe that such sites would be electrified most cost-effectively through grid connection. Data on existing grid infrastructure were gathered from the reports of different consultants and from the utility. Efforts were made to assess demand based on current usage patterns, but this was extremely difficult owing both to the general challenges of latent demand estimation and to the recent conflict in the country, which resulted in large amounts of unregistered auto generation, very high grid prices (which likely depress demand), and an overrepresentation of wealthy households among grid-connected individuals. The model eventually settles on a scale of demand from 300 kWh per household per year (in the smallest communities) to 2,400 kWh per household per year (in Monrovia), based on estimates of appliance use and workshops. The model accounts for increasing demand among connected households (2.34 percent per year) based on population growth as well as conversations with practitioners. It uses capital costs from recently completed projects or from actual costs of projects in other countries. A novelty of this model is that because of the electricity interconnection with Côte d'Ivoire and the existence of the grid in Monrovia, the model actually builds out the grid in two areas before eventually connecting them.

The model finds that, after 30 years and achievement of 100 percent urban access and 70 percent rural access, 93 percent of households are connected to the grid, with the rest using distributed generation. That said, the model also notes the value of using small distributed systems to provide households with electricity access while the grid is being rolled out. To address the cost of connecting people twice, the model suggests that distributed systems should be built to half the capacity specified in the model. The model notes that because of its phased approach its accuracy is likely greatest for the first five years and decreases after that. Consequently it calls for updating the findings as electrification is rolled out.

[31] These goals are based on the goals of the Liberian government.

Even though the model aims for only a 70 percent rural electrification rate, it is notable for the high percentage of grid connections it predicts as cheapest. This is despite the highly dispersed nature of the Liberian population: 30 percent of all settlements have populations of fewer than 25 people, 65 percent have fewer than 100 people, and 99.9 percent have fewer than 5,000 people.

Kemausuor et al. (2014) uses the Network Planner model to look at the case of Ghana, where it models the least-cost technology allocations for achieving 100 percent electricity access by 2020 using 2010 as a base year. The model compares grid electrification, mini-grid diesel generators, and stand-alone PV (complemented by a diesel generator for productive use). Deriving demand as a function of population size and income, the model uses a base domestic demand of 150 kWh per household per year, with another 19.5 kWh per household per year for productive use. It is based on initial population densities and average household size and accounts for different rates of population growth in rural and urban areas. It also allows for greater demand from households located in more densely populated areas. The location of communities comes from 2000 census data, extrapolated to 2010 using population growth rates obtained from the Ghana Statistical Service (GSS). The GSS also provided data on the location of electrified settlements. The work assumes a mean standard household distance of 25 meters and includes allowances for electricity use by elementary and high schools (institutions larger than these were expected to exist only in already electrified areas).

To achieve the least-cost electrification, the model allocates 85 percent of new connections to the grid,87 percent to mini-grids, and 7 percent to stand-alone PV (Table A3).

Table A3. Results from Kemausuor et al. (2014)

Indicator	Grid	Mini-grid diesel	Stand-alone PV
% of communities electrified by technology	85	8	7
Total cost (US$)	591,220,000	57,648,000	46,537,000
Cost per household (US$)	2,080	3,190	3,480

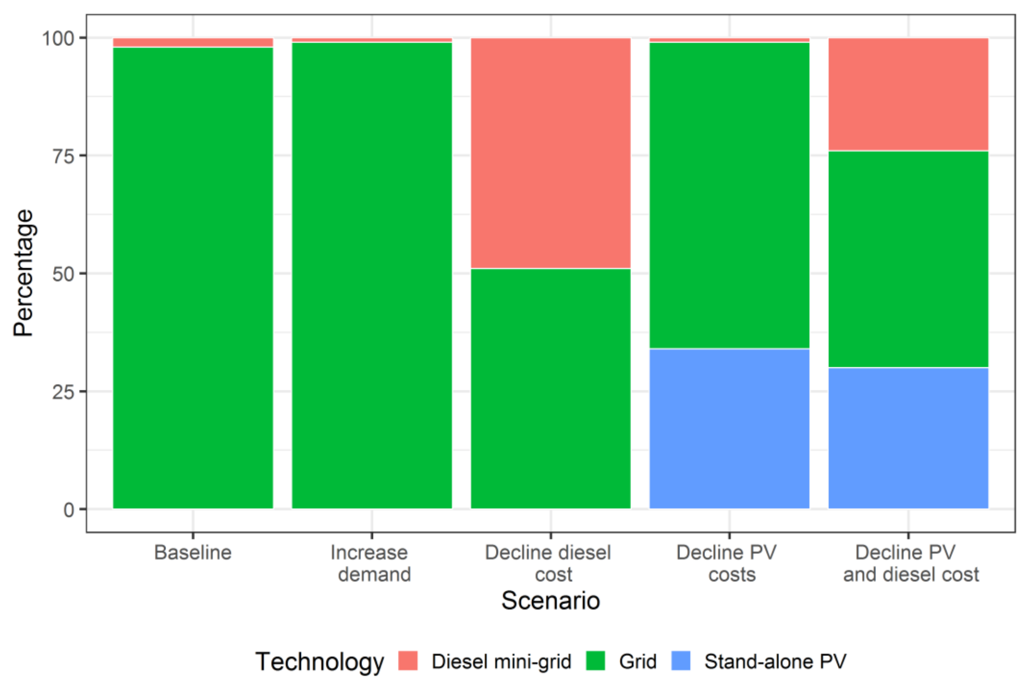
Note: Kemausuor et al. (2014) applied the model to 2,600 communities.

The model finds that a grid connection is the cheapest electrification option for a large share of communities, and the authors explain this outcome by pointing to Ghana's relatively extensive grid and historic efforts focused on energy access. They also note that financing costs in the study are relatively high because they look at achieving energy access in only 10 years. They explain that expected cost declines in renewable technologies should lead to an increase in the uptake of distributed technologies.

Ohiare (2015) uses the Network Planner model to consider the least-cost electrification pathway in Nigeria to 2030, comparing stand-alone systems using PV and a diesel generator for productive use, a diesel-based mini-grid, and grid electrification. Because of a lack of data on population, the model operates at the scale of broad administrative areas. They consider 774 local government areas, treating each as a settlement and assuming them to be homogenous throughout, with an assumed mean household distance of 25 meters. The paper assumes average household demand is 330 kWh per household per year and considers distinct rates of population growth for urban and rural households, which drive increases in demand across settlements over time.

The model shows that 98 percent of currently unconnected households would be most cheaply connected by the grid. Mini-grids account for the remaining 2 percent of connections (Figure A2). The model makes clear that there is significant variation within the country with regard to technology allocation: the smallest role for grid connections is 65 percent in the most sparsely populated local government area.

Figure A2. Results from Ohiare (2015): Technology allocation across multiple scenarios



Source: Visualization derived from Ohiare (2015).

The model then runs scenarios in which household demand is increased (to 400 kWh per household), diesel prices are reduced (from $0.96 to $0.65 per liter), and solar prices are reduced (by 250 percent[32]). Increasing household demand has the expected effect of pushing more people onto the grid. Notably a significant reduction in solar prices reduces the proportion of households for whom the grid is the cheapest option to 65 percent of households, with diesel mini-grids becoming the cheapest option for 34 percent. Lowering the prices of both diesel and solar drops the proportion of grid connections to 46 percent, while mini-grids move to 24 percent and stand-alone PV/diesel moves to 30 percent (Figure A2).

Again, the model is notable for allocating a large proportion of unelectrified households to the grid for least-cost electrification, even under a large decline in solar prices. This result is likely due to Nigeria's high population density and also partly to the use of local government areas as the level of analysis, which omits details about highly isolated and remote settlements. Including such settlements would be expected to increase the role of stand-alone PV, although the numbers would likely be insubstantial.

The **OnSSET** model is developed principally by the Royal Institute of Technology at Stockholm (KTH) along with other partners.[33] The model is built on a gridded population density map[34] that breaks down the region being modeled into evenly sized cells, with each cell allocated a number of people. The model then adopts a specific demand target and calculates the resultant demand for each cell.

In terms of technology allocation, the model builds on a method developed by Fuso Nerini et al. (2016), which determines the LCOE for different technologies across a variety of relevant parameters,[35] using standard estimates of capital costs for generators (see a longer discussion on Fuso Nerini et al. 2016 below). Notably, Fuso Nerini et al.'s model applies a constraint on the grid, assuming that no new HV transmission lines could be built cost-effectively. Thus the model limits the possibility for grid expansion to MV lines, which it assumes cannot be extended beyond 50 km from the existing grid. Only households within 50 km of the existing grid are liable to be electrified by a grid connection. For all of the rest, only distributed technologies are compared. For households that are identified as needing to be grid connected, the model uses a minimum spanning tree algorithm to connect all the cells along a single piece of infrastructure.

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32 This takes solar prices from $2,000/kW in the baseline to $500/kW.

33 These partners are the United Nations Department of Economic and Social Affairs, the United Nations Development Programme, the World Bank, ASEA Brown Boveri, the International Energy Agency, the US National Aeronautics and Space Administration, the Swedish Research Council (Vetenskapsrådet), the Swedish International Development Cooperation Agency, and the Energy Sector Management Assistance Agency.

34 Different publications use different resolutions.

35 These include household demand, population density, distance to the grid (a maximum of 50 km), cost of electricity from the grid, availability of renewable resources (solar, wind, and whether hydro potential exists within 10 km of the settlement), whether a large-scale source of biomass exists within 10 km of the settlement, diesel price, and capital cost of generation technologies.

Based on these calculations, the OnSSET model then calculates the LCOE for each technology for each cell based on its characteristics: population density, desired level of access, distance from the grid, renewable resources, and fuel costs. To do so, it first considers the demand from each cell and compares this with Fuso Nerini's (2016) reference calculations to determine whether the cell meets a minimum demand to warrant connection to the grid. This is done for each cell, with the distance from the grid increasing for each subsequent cell by the size of each cell, up to 50 km from the grid (owing to the limit placed on MV lines). Once one area is connected to the grid it becomes cheaper to connect a subsequent area, and the model accounts for this by iterating this process until no more cells can sustain a connection to the grid. The computational intensity of this process is limited by the assumption that the grid can be extended only by 50 km.

The model then considers all the remaining unconnected cells and calculates the LCOE for the variety of distributed technologies being assessed by the model, again using the cost calculations provided by Fuso Nerini et al. (2016). The model selects the technology with the lowest LCOE and matches it to the cell.

The OnSSET model can effectively provide high-resolution data on where different technologies will prove to be least cost, and it does not suffer from the need for settlement data that drives the Network Planner model and causes it to ignore isolated households. The OnSSET model is also able to account for the fact that every time a household becomes grid connected, the cost of connecting a subsequent household decreases. Publications using the OnSSET model limit the length of grid extension to 50 km from existing infrastructure, limiting the scope for grid expansion. This parameter can be changed within the model, although doing so would raise greater computational challenges during the network optimization step of the model. Likewise, the model likely biases results toward distributed technologies because it considers whether any cell can sustain a grid connection before shifting to distributed technology. This approach means that the lowest-cost technology is not always chosen, but rather that the grid is chosen only if it can be sustained at a breakeven price, before more expensive distributed generation is chosen.

Mentis et al. (2015) uses the OnSSET model to consider a scenario in which Nigeria achieves 100 percent electricity access by 2030. The model is built on a population density map composed of 2.5 km × 2.5 km cells; it uses demand levels of 350 kWh per capita per year for urban areas and 170 kWh per capita per year for rural areas.[36] The model accounts for population growth, differentiating growth rates in rural and urban areas. It uses the AfDB infrastructure map to attain geolocated data on the spatial extent of the existing

[36] Assuming five people per household, this translates to 1,750 kWh per household per year in urban areas and 850 kWh per household per year in rural areas. This is tier 4 access for urban areas and tier 3 access for rural areas, according to the World Bank Multi-Tier Framework.

grid infrastructure. The model determines the location of the (un)electrified households by overlaying the geospatial grid on top of the population density map and assumes that all of the electrified population (derived from the electrification rate, according to the IEA) live next to the grid. It builds a buffer around the existing grid until that buffer covers the number of people identified as having electricity access in Nigeria. The grid is then expanded to connect all planned power stations, as well as future mines (which are identified from United States Geological Survey data).[37] These connections are undertaken using MV power lines where possible and HV lines where necessary. Outside of extending the grid to planned power stations and mines, the model limits grid extension to within 50 km of the existing grid.

The model considers the following technologies: stand-alone PV; stand-alone diesel; PV, wind, hydro, and diesel mini-grids; and the grid. Diesel fuel costs come from the national price plus the cost of transporting fuel to the cell, determined based on travel time data from the nearest city provided by the European Joint Research Center. Wind and solar energy potentials are taken from the International Renewable Energy Agency (IRENA). A lack of data on hydroelectric potential is addressed by using hydrological potential, which is aggregated at the level of Nigerian states.

The model finds that 85.6 percent of unconnected households in Nigeria would be most cheaply connected by the grid, 14.3 percent by mini-grids, and 0.3 percent by stand-alone PV. Among the mini-grids, diesel dominates, followed by PV. Small hydro, wind and stand-alone systems play almost no role. Among stand-alone systems, diesel marginally dominates (Table A4).

Table A4. Results from Mentis et al. (2015)

		Mini-grid				Stand-alone	
Indicator	Grid	Diesel	PV	Wind	Hydro	Diesel	PV
% of households connected by technology	85.60	7.97	4.78	~ 0	1.56	0.16	0.13

The model is further sensitivity-tested by varying rural demand to as low as 150 kWh per capita per year and as high as 190 kWh per capita per year.[38] The impact on results is small (Table A5).

Table A5. Sensitivity test from Mentis et al. (2015)

	% of households connected by:		
Rural demand level	Grid (%)	Mini-grid (%)	Stand-alone (%)

[37] This is done to reflect that such infrastructure development forms part of the AfDB's infrastructure planning (Mentis et al. 2015).

[38] These levels are equivalent to 750 and 950 kWh per household per year.

150 kWh per capita per year	85.49	13.50	1.01
170 kWh per capita per year (baseline)	85.66	14.04	0.30
190 kWh per capita per year	85.90	13.97	0.13

Note: Urban demand is held constant at 350 kWh per capita per year.

The model is notable for producing a large amount of grid connections and suggesting a very small role for wind and hydro. Considering the 50-km limit on grid connections, the large number of grid connections produced by the model indicate the extent to which the Nigerian population resides in close proximity to the existing grid infrastructure.

Finally, this model is based on capital costs used by Fuso Nerini et al. (2016) that precede the recent steep declines in solar components (F. Fuso Nerini, personal communication, March 13, 2018). The precise impact on the technology allocation of using reduced PV and battery prices is not clear, but one would expect that distributed technologies would become the least-cost option both closer to the grid and at higher levels of demand.

Mentis et al. (2016) use the OnSSET model to repeat the analysis in Ethiopia. The only slight differences in the analysis are that rural demand is set at 170 kWh per capita per year, while for urban areas it is 300 kWh per capita per year.[39] Further, hydroelectric potential is estimated based on an assessment of elevation, river locations, and streamflow characteristics.

The results of the model allocate 93.4 percent of the newly connected population to the grid, 5 percent to mini-grids, and less than 1 percent to stand-alone systems (Table A6). Further, the mini-grid systems are again dominated by diesel and PV, with wind and hydro playing a very small role. The split between diesel and PV is almost equal in the case of stand-alone systems.

Table A6. Results from Mentis et al. (2016)

		Mini-grid				Stand-alone	
Indicator	Grid	Diesel	PV	Wind	Hydro	Diesel	PV
% of households connected by technology	93.41	1.37	0.95	0.3	0.66	0.23	0.27

39 Assuming five people per household, this translates to 850 kWh per household per year for rural areas and 1,500 kWh per household per year for urban areas. This is tier 3 access for rural areas and tier 4 access for urban areas, according to the World Bank Multi-Tier Framework.

The results are again sensitivity-tested—this time against a single scenario in which rural demand is dropped to 50 kWh per capita per year.[40] The result is an equal shift of about 5 percent each from the grid and mini-grid systems to stand-alone systems (Table A7).

Table A7. Sensitivity test from Mentis et al. (2016), comparing grid, mini-grid and stand-alone technologies, across baseline and low-demand scenarios

	% Households connected			% Financing cost		
Scenario	Grid	Mini-grid	Stand-alone	Grid	Mini-grid	Stand-alone
Baseline	93.41	5.65	0.94	83.21	15.2	1.59
Low Demand	88.9	0.35	10.75	NA	NA	NA

Note: The Baseline scenario is the same as Table A6 grouped to reflect how findings were published. Percent of financing costs were published for this model and are included here for completeness sake.

The model again produces high allocations to the grid, even considering significantly lower rural demand. This result is even more notable given the currently low access rates in Ethiopia (26 percent overall and only 10 percent in rural areas).

Mentis et al. (2017) then applies the OnSSET model to consider all of sub-Saharan Africa. The model's parameters are updated in an attempt to increase its accuracy. Changes include (1) increasing the resolution of the population density map to 1 km × 1 km, (2) modifying grid expansion costs by a factor to account for the increased cost of building the grid in challenging terrain or far from roads, (3) including proximity to coastlines when estimating the diesel price, and (4) updating the capital costs to better reflect the recent cost declines in renewables. Instead of identifying the unelectrified population through the use of energy access rates and proximity to the existing grid, the model uses nighttime illumination data to identify electrified areas. The model also undertakes a slightly different evaluation, considering all of the different tiers of energy access, applying them homogenously across rural and urban populations as different scenarios. The model further considers two scenarios regarding the global price of diesel (low price = $47 a barrel; high price = $113 a barrel[41]).

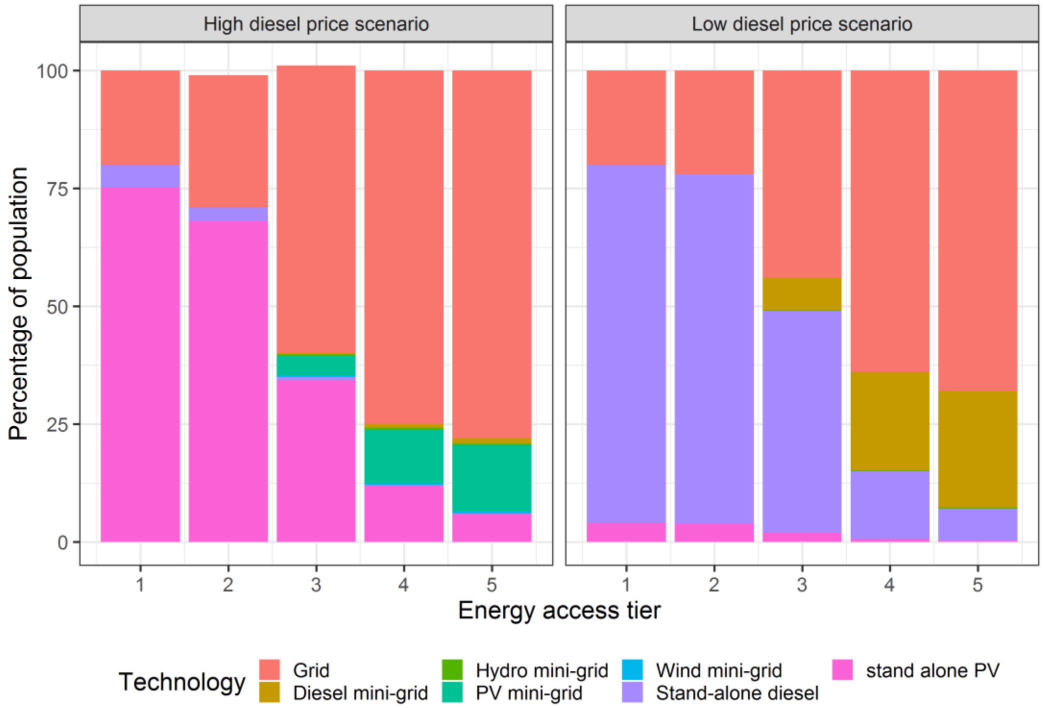
The results show that for a tier 3 level of access (a measure comparable to that used in other models), the proportion of the population most cheaply connected to the grid lies between 44 and 61 percent, depending on the diesel price, with increased diesel prices resulting in a larger role for the grid. At a tier 3 level of access, the model connects between 5 and 7 percent of households to mini-grids and between 35 and 49 percent of households to stand-alone technologies. In

[40] This is equivalent to 250 kWh per household per year, or the IEA minimum for rural areas.

[41] These prices are taken from the IEA new policies scenario (IEA World Energy Outlook 2015).

both cases the proportion of the population served by distributed systems declines as diesel costs increase. The results are summarized in Figure A3.

Figure A3. Results from Mentis et al. (2017): Technology allocation across demand tiers and oil price scenarios



Source: The graph is derived from Mentis et al. (2017). Rounding errors cause certain scenarios not to sum to 100.

The results also illustrate that diesel dominates the distributed technologies in all cases where oil prices are low, with mini-grids playing a larger role under higher demand scenarios. At high oil prices, PV is the dominant source of distributed generation in all cases, with the role for mini-grids again increasing at high levels of demand.

The model results make clear how increasing demand shifts technology allocations from stand-alone (80 percent of connections at tier 1, regardless of the diesel scenario) toward the grid (68–78 percent of connections at tier 5, depending on the diesel price). Again, the model predicts a very limited role for distributed wind and hydro despite their low costs and shows a relatively limited role for mini-grids.

The International Energy Agency (2017), in its special report *Energy Access Outlook 2017*, models the entire unconnected population globally. It does not publish the workings of the model in comprehensive form,[42] but it does refer to collaboration with KTH Royal Institute of Technology[43] (which developed the OnSSET model, results for which are published by Mentis et al. 2015, 2016, 2017 and Moksnes et al. 2017). The IEA also notes that its analysis of sub-Saharan Africa takes place at the level of 1 km^2—the same as that used by Mentis et al. (2017). In its discussion of methodology, the IEA points out that the model, which runs to 2030, accounts for population growth, economic growth, urbanization rates, and the availability and price of different fuels. It considers decreasing technology costs, but it does not assume any technological breakthroughs. It assumes rural demand of 250 kWh per household per year and urban demand of 500 kWh per household per year, though these are set to increase to national averages. The published results from this analysis do not show the proportion of people to be connected by each technology based on least cost, but rather the proportion of financing that needs to flow to grid, mini-grid, and stand-alone. Although not stated explicitly in the methodology, the report mentions solar PV, wind, hydropower, and diesel technologies for mini-grids as well as diesel and solar PV for stand-alone systems. Again, these are the same as the technologies considered within the OnSSET model. It is not clear whether the IEA limits grid extension to within 50 km of the existing grid.

The results of the model show that, following a least-cost approach, investments should be made in the following proportions: 25.6 percent to stand-alone, 41.6 percent to mini-grids, and 32.7 percent to the grid. Based on figures presented in the report, we can estimate the proportion of people connected by different technologies[44]: approximately 26 percent to stand-alone, 35 percent to mini-grids, and 39 percent to the grid (Table A8).

[42] Current information on methodology is limited to IEA (2017b); our emails to the IEA requesting more information have gone unanswered.

[43] This reference is as follows: "The geographic analysis of the type of access that contributes to electrification pathways has been developed in collaboration with the KTH Royal Institute of Technology, Division of Energy Systems Analysis (KTH-dESA) in Stockholm, Sweden. (pp.6 – page numbers not explicit in document)"

[44] This is estimated by combining the numbers from Figure 2.5 (p. 50) and Figure 2.7 (p. 53) from the Energy Access Outlook (2017) Energy Access Outlook 2017: From poverty to prosperity, World Energy Outlook Special Report, Paris, France: International Energy Agency.

Table A8. Results from IEA (2017)

Indicator	Technology		
	Grid	Mini-grid	Stand-alone
% of financing flowing to technology	32.69	41.55	25.76
% of people connected by technology[a]	39.15	34.88	25.97

[a] Estimated from figures in IEA (2017). See footnote 14.

What is notable in the findings from the IEA model is the smaller role for the grid and the much larger role for mini-grids. Such findings are even more surprising given the extent to which the IEA model is based on the OnSSET model and the fact that the IEA model uses lower levels of demand than was used in the OnSSET model for sub-Saharan Africa – though these do increase to the national average. One potential explanation could be that higher population densities in Asia drive larger numbers of mini-grid connections, though no explanation is provided in the model.

Moksnes et al. (2017) applies the OnSSET model to consider the least-cost electrification pathway for Kenya. The model is built on top of the 1 km × 1 km population data set that informs the IEA and the sub-Saharan Africa models produced by Mentis et al. (2017). Like other OnSSET models, the model considers the grid, mini-grids (wind, hydro, PV, diesel), and stand-alone (PV, diesel) technologies. Finally, the model uses current capital costs for renewables, and thus those costs reflect the recent cost declines for renewables.

The model runs a high- and low-demand scenario. The low-demand scenario assumes rural demand of 43.8 kWh per capita per year and urban demand of 423 kWh per capita per year. For the high-demand scenario, rural demand is 423.4 kWh per capita per year and urban demand is 598.6 kWh per capita per year.[45] Note that for the low-demand scenario, this translates into a tier 2 level of demand in rural areas, while in urban areas it is a high tier 4 level of demand. For the high-demand scenario, this equates to high tier 4 in rural areas and tier 5 in urban areas. These numbers are derived from the Kenyan Power Generation and Transmission Master Plan. Like other iterations of OnSSET, the model accounts for population growth as a source of increased demand.

The study innovates, however, by using the output from the OnSSET model to drive another model (the OSeMOSYS model), which is used to determine the grid price for Kenya by considering the country's broader electricity development

[45] These rates are equivalent to the following rates per household per year: low demand, rural areas, 219 kWh; low demand, urban areas, 2,115 kWh; high demand, rural areas, 2,117 kWh; and high demand, urban areas, 2,993 kWh.

ambitions and optimizing the grid.[46] In this setup, the OnSSET model uses a current grid price of $0.125 per kWh to determine the split between grid connections and distributed generation. The increased demand on the grid that derives from the new grid connections is then fed back into the OSeMOSYS model, which considers the available resources in Kenya, as well as the national demand profile and energy expansion plans, to determine an updated grid price. This price is then fed back into the OnSSET model to see how it affects further grid connections. This process is repeated only one time. The result is a grid price of $0.08 per kWh across both the high and low demand scenarios. The model also innovates by identifying unelectrified populations, which it derives from a mix of nighttime illumination data and geolocated road and grid infrastructure data, along with the national electrification rate.

The results from the model show that for both the low- and high-demand scenarios, grid connections dominate, but only by a small margin in the low-demand scenario, where the grid accounts for 53 percent of new connections (Table A9).[47] In the high-demand scenario, the grid connects 90 percent of the population. Mini-grids play no role in the low-demand scenario, while stand-alone diesel and PV systems both make significant contributions. The authors point out that diesel dominates in areas near roads and cities, while PV dominates in more remote regions as transport costs increase. For the high-demand scenario mini-grids dominate the distributed technologies, with diesel mini-grids playing the largest role.

Table A9. Results from Moksnes et al. (2017)

Scenario	% of population connected by technology						
	Grid	Stand-alone		Mini-grid			
		Diesel	PV	Wind	Diesel	PV	Hydro
Low demand	53.40	27.30	19.29	0.00	0.00	0.00	0.00
High demand	90.40	0.55	1.68	0.02	7.30	0.00	0.06

The authors test the sensitivity of the model to changes in the discount rate, shifting it from 9.8 percent to 5.75 percent. Doing so changes the on-grid generation technologies articulated in the OSeMOSYS model (away from low-capital, fuel-based systems toward high-capital, renewable systems). However, the authors do not describe any impact on the technology choices aimed at achieving access (i.e., the technology allocation described by the OnSSET model). The authors further examine the impacts of reducing the grid cost from

[46] A full assessment of the OSeMOSYS model is beyond the scope of this work; readers are directed to the original Moksnes et al. (2017) paper for further details on its functioning and accuracy.

[47] The numbers for this table had to be obtained from the author because they are not published in the paper (N. Moksnes, personal communication, April 30, 2018).

$0.125 to $0.08 per kWh: in the high-demand scenario, reduced prices result in an increase of 1.22 million people to the grid, and in the low demand scenario, an increase of 1.67 million people. Based on this finding, the authors note that the model underestimates grid connections owing to the limited number of iterations between the OnSSET and OSeMOSYS models. More iterations would serve to drive down grid prices further and therefore increase grid connections.

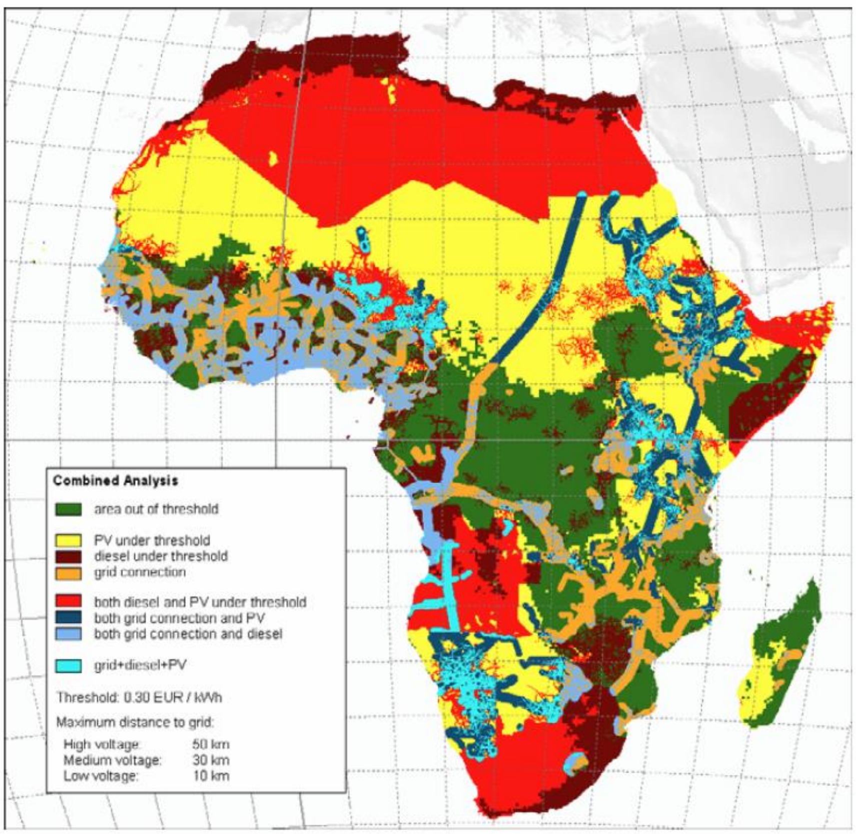
The paper is notable for the large differences it produces when comparing high- and low-demand scenarios. The demand levels modeled are both on the high and low end of the scale compared with other models assessed in this report. Regardless of issues of demand, however, the model suggests that the role for mini-grids is low to nonexistent in the low-demand scenario.

Having discussed the Network Planner and OnSSET models, this appendix proceeds to discuss the remaining individual publications of model results considered in this work.

Szabó et al. (2011), as the first geospatial model generated at the continental level, adopts a simple mapping approach to estimate the distribution of different technologies across all of Africa. The approach does not constitute a dynamic model, but sets a specific price for electricity (€0.3 per kWh) and then maps which technologies can achieve this price in which geographies. As a result the model does not produce a proportional split in the number of connections per technology, but instead produces a map showing which technologies are capable of providing electricity at a plausibly affordable price (Figure A4). This map is complemented by a table that describes the number of people who could be connected to each technology at a price below €0.3 per kWh. Subsequent correspondence revealed that this was calculated based on a 1 km^2 population grid (M. Moner-Girona, personal communication, January 15, 2019).

The approach considers grid extension, diesel generation, and solar PV. Technically, the approach is a comparison only between the grid and mini-grids because the costs of metering and distribution lines are thought to be common across technologies. The analysis does not estimate population density or demand, but rather estimates cost in the following way. For the grid, the model simply assumes that all households within 90 km of the grid could be connected for less than €0.3 per kWh. The authors attained geospatial information on the grid from a number of sources: free web sources, databases, regional institutes, and individual experts. They point out that despite these efforts the database is incomplete, unevenly covering 33 of the 48 countries. For solar PV and diesel, the model determines the LCOE by considering only the cost of generating electricity from generation sources of a particular capacity; this is the non-demand approach to estimating LCOE described at the start of the report. For example, for solar PV the analysis considers a 4 kW_p–15 kW_p system.[48] It places further requirements on the system: demand will consist of one-third daytime use and two-thirds evening use, and the system is designed with a battery so as not to fail on more than 5 percent of days. The analysis then works out the LCOE of energy from such a system, dividing its costs by the energy it will produce. The same approach applies to diesel, where the analysis considers diesel generators of between 4 and 15 kW and determines the LCOE based on the efficiency of the system, capital costs, fuel costs, O&M, discount rate, and system lifetime. Fuel costs vary by distance to the nearest town. The results of the analysis are shown in Figure A4.[49]

Figure A4. Results from Szabó et al. (2011): Areas in which different technologies can supply electricity at €0.3/kWh



Source: Szabó et al. (2011, 63).

[48] Based on this peak level, and an assumption that each generator would serve 30–140 households with each generator producing 35–130 MWh per year, the model implicitly assumes that household demand will be between 250 and 1,000 kWh per year (tiers 2–4) (M. Moner-Girona, personal communication, January 15, 2019).

[49] The authors also undertake this analysis for a price of €0.25 per kWh, not shown here.

Szabó et al. (2013) builds on the above analysis, again considering Africa but generating a dynamic model that determines the least-cost technology. The model is built on top of a 1 km × 1 km population grid and compares the grid, hydroelectric mini-grids, stand-alone PV, and stand-alone diesel. The updated model accounts for recent cost declines in solar modules; uses new diesel prices; uses hourly, rather than daily, insolation data; and assumes all planned grid extension has been completed. The analysis again considers travel time to nearby towns in order to determine diesel prices and uses an oil price of $85 a barrel, which produces similar electricity prices to the 2011 analysis. The authors attempt to update the georeferenced electricity grid data, but again they note that the data set remains incomplete, with uneven coverage among the 48 countries in sub-Saharan Africa.

Like the 2011 analysis, the model does not consider any sort of demand estimate but rather calculates LCOE based on generator size. For solar PV, this is a 15 kW_p system, supporting a load profile of two-thirds in the evening and one-third in the daytime, designed to fail on not more than 5 percent of days.[50] For diesel, the method considers diesel generators of 4–15 kW. For mini-hydroelectric, no database is available for Africa, and so the model derives suitable sites by combining a digital elevation model and data on mean annual river discharge. The system is sized to be at least equal in capacity to the energy produced by the 15kW_p PV system. Because the system has the advantage of continuous production, the LCOE is just below €0.15 per kWh. The LCOE for mini-hydro in any given pixel[51] is then calculated by adding the LCOE of generation with a cost for connecting that pixel to the hydro generator, based on its distance from the generator. This cost is based on a standard amount: €0.025 per kWh per km. For the grid, the LCOE is calculated in a manner similar to hydro, with the cost of generation coming from World Bank data on electricity tariffs in each country, and a uniform cost of grid extension of €0.025 per kWh per km. The LCOE for each pixel is then the cost of generation plus the cost of connection.

Notably, the results of the model do not look at the process of connecting currently unconnected households, but rather at what the technology distribution would be if everyone were connected using the technology with the lowest LCOE. As a result the model overestimates the number of grid connections; if the model considered only those populations that had yet to be connected, all the populations that are currently grid connected would be ignored. The results show that, based on 2012 prices, 34 percent of people will be connected to solar PV, 15 percent will be connected to diesel generator, 12 percent will be connected to

[50] Based on this peak level, and an assumption that each generator would serve 30–140 households with each generator producing 35–130 MWh per year, the model implicitly assumes that household demand will be between 250 and 1,000 kWh per year (tiers 2–4) (M. Moner-Girona, personal communication, January 15, 2019).

[51] The paper does not make clear the resolution at which calculations take place, with different input data sets having different resolutions.

mini-hydroelectric, and 39 percent will be connected to the grid (derived from Figure 9, p. 507).

Compared with other assessments, these results are significant for the relatively small role they suggest for the grid and the large role they suggest for hydro. Such results are even more remarkable when one considers that they overestimate the grid contribution for the reason just described, and they use renewable component costs from 2012, whereas more recent models indicate a larger role for the grid using lower prices. It is difficult to explain why these findings differ so substantially from the rest of the literature. The only obvious explanation is the use of a relatively low discount rate (5 percent), which likely skews the model toward distributed systems.

Moner-Girona et al. (2016) models the least-cost electrification pathway for Burkina Faso. The model is built on settlement data retrieved from the national statistical agency and draws data on the location of existing and planned grid infrastructure from a number sources in Burkina Faso. The model compares the following technologies: grid, hydropower mini-grid, PV mini-grid, stand-alone PV, and stand-alone diesel. For stand-alone diesel, the model accounts for the costs of transporting diesel from the nearest town. The location of electrified settlements comes from the utility, although these data do not include information on which households in those settlements are connected to the grid (M. Moner-Girona, personal communication, October 16, 2018). Data on demand are poor in the country, so the model assumes demand of 40 kWh per capita per year[52] with a 4 percent annual increase. It assumes a demand profile in which one-third of electricity is consumed during the day and two-thirds are consumed in the evening. PV systems are built based on this demand profile and sized to fail on not more than 5 percent of days per year. The model also accounts for demand from social infrastructure, which also increases but has a demand profile opposite to that of residential users. For hydro systems, the model derives suitable hydro sites from digital terrain data as well as data on stream characteristics and catchment size.

The model works by calculating the cost of distributed generation for a grid of 1 km × 1 km cells across the entire country. The model selects the least-cost technology, considering capital costs, diesel price (including the transport price), availability of the renewable resource, the cost of generation from hydro (estimated at €0.15 per kWh), and the distance of the cell from the nearest potential hydroelectric source (which is multiplied by a cost for grid extension estimated at €0.025 per kWh per km). The cheapest technology is then compared with the cost of access via the grid, which is calculated based on the distance of the cell from the grid and the cost of undertaking that extension

[52] This level is equivalent to 200 kWh per household per year.

(estimated at €40,000 per km, based on real assessments of other projects in Burkina Faso). The least-cost technology is then selected.

The model finds that 60 percent of the population living in nonelectrified communities are most cheaply connected by distributed generation. Notably, all of these connections are established via PV systems, with no role for hydro or diesel. When the model considers whether demand at each center will effectively be greater than can be supplied by a 15 kWp system (which is used to define mini-grids), it finds that 98.4 percent of PV connections are most effectively provided by mini-grids.

Table A10. Results from Moner-Girona et al. (2016)

Indicator	Technology				
	Grid	PV mini-grid	PV stand-alone	Diesel	Hydro
% of unelectrified population connected by technology	40.00	59.04	0.60	~ 0	~ 0

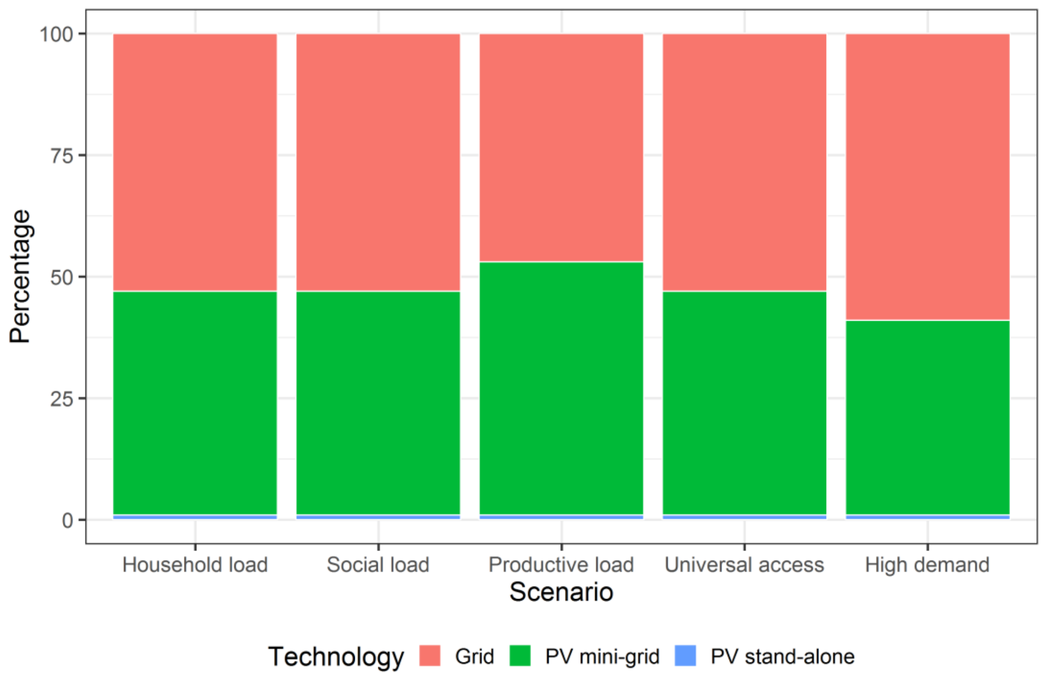
The model is notable for the large percentage of connections to distributed generation and the large role for mini-grids—a result that is especially surprising given the low demand used—as well as for the negligible role for diesel systems. The large role for distributed connections can be explained in part by the very low level of demand (40 kWh per capita per year), which is lower than the rural minimum standard set by the IEA (and is equivalent to tier 2 in the World Bank Multi-Tier Framework for measuring energy access). Furthermore, the model uses only a 5 percent discount rate for finance—the lowest rate of any of the models assessed.[53] The unpublished sensitivity tests to increasing the discount rate had large impacts on the allocation of technologies (M. Moner-Girona, personal communication, October 16, 2018). At the same time, however, it should be noted that this model does not include the generation cost from the grid. Including this cost reduces the role of the grid to almost nothing, because grid tariffs in Burkina Faso are high, around €0.21 per kWh (M. Moner-Girona, personal communication, October 16, 2018). When calculating mini-grid suitability, the model does not include any of the costs of distribution. Rather it simply allocates mini-grids based on the amount of demand generated by a settlement. Finally, the surprisingly small role for diesel is thought to be due to the high cost of diesel in Burkina Faso. Moreover, the study was undertaken at a time when global petroleum prices were high.

The model undertakes sensitivity testing for the following scenarios: (1) household load dominates the settlement demand profile, (2) 10 percent of the

[53] This low rate was used because it was the cost of finance being supplied by the European Development Bank when providing climate finance (M. Moner-Girona, personal communication, October 16, 2018).

load in the settlement demand profile is due to social infrastructure, while household load makes up the remainder, (3) productive uses are included so that the load profile is 40 percent productive, 10 percent social, and 50 percent household, (4) a universal access scenario in which demand increases only in unelectrified settlements, and (5) a high-demand scenario in which demand increases to 110 kWh per capita per year in electrified settlements and to 40 kWh per capita per year in settlements without access to electricity. The results are shown in Figure A5 (these results pertain to the total coverage of the population once 100 percent electrification has been reached, not the proportion of the newly connected population, which is given in Table A10).

Figure A5. Results from Moner-Girona (2016): Sensitivity test on least-cost technology allocation for Burkina Faso



Source: Derived from Moner et al. (2016).

Deichmann et al. (2011) models energy systems across Ethiopia, Ghana, and Kenya. The authors compare grid extension with stand-alone (solar PV, wind, and diesel) as well as mini-grid (diesel, wind, solar PV–wind, and biodiesel) technologies. The model is built on settlement data, with each settlement treated as a demand node. It assumes one high static level of demand across all households—120 kWh per household per month (1,440 kWh per year), which is on the low end of tier 4 access. The model does not focus on unelectrified settlements but rather determines the electrification pathway as if the entire population were unconnected to start with—i.e., the model builds the grid from scratch.

The model works by seeking to connect the largest demand centers to one another.[54] Once a demand center is connected, it is assumed that every settlement within 120 km of that demand center can be serviced by LV power lines. The model continues to connect demand centers until every settlement in the country is covered by the grid. To address the computational problems of network optimization, the model deploys a variation of Prim's algorithm to solve for a minimum spanning tree based on a "greedy algorithm" by which the connection with the highest "payoff" is selected (minimizing distance and maximizing the number of people connected). The model then proceeds to connect every settlement, in order of decreasing "payoff." By calculating the cost of connecting each additional settlement, the model derives the marginal cost of grid extension (which rises as increasingly distant and less populated settlements are connected).

The model then calculates LCOE for all demand nodes for all of the distributed technologies considered by the model (however calculations are done for wind only if the wind resource at a demand node meets a minimum threshold). The model then compares and selects the distributed generation source with the LCOE in every settlement. This LCOE is further compared with the marginal cost of connecting a given settlement to the grid, with distributed generation sources being selected when the LCOE is below the marginal cost.

It is important to note that this model does not calculate the LCOE for currently unconnected households, but rather a theoretical number regarding the proportion of people who would be connected if the system started from scratch. The model is therefore likely to overestimate the number of grid connections, because many of the grid connections identified by the model describe households that are already connected to the grid. Moreover, this model does not seem to account for the fact that the optimally designed grid network generated by the first run of the model will interact with the technology allocation. Thus the model is liable to produce a suboptimally designed grid network that would increase grid costs and possibly misallocate demand centers to the wrong technology.

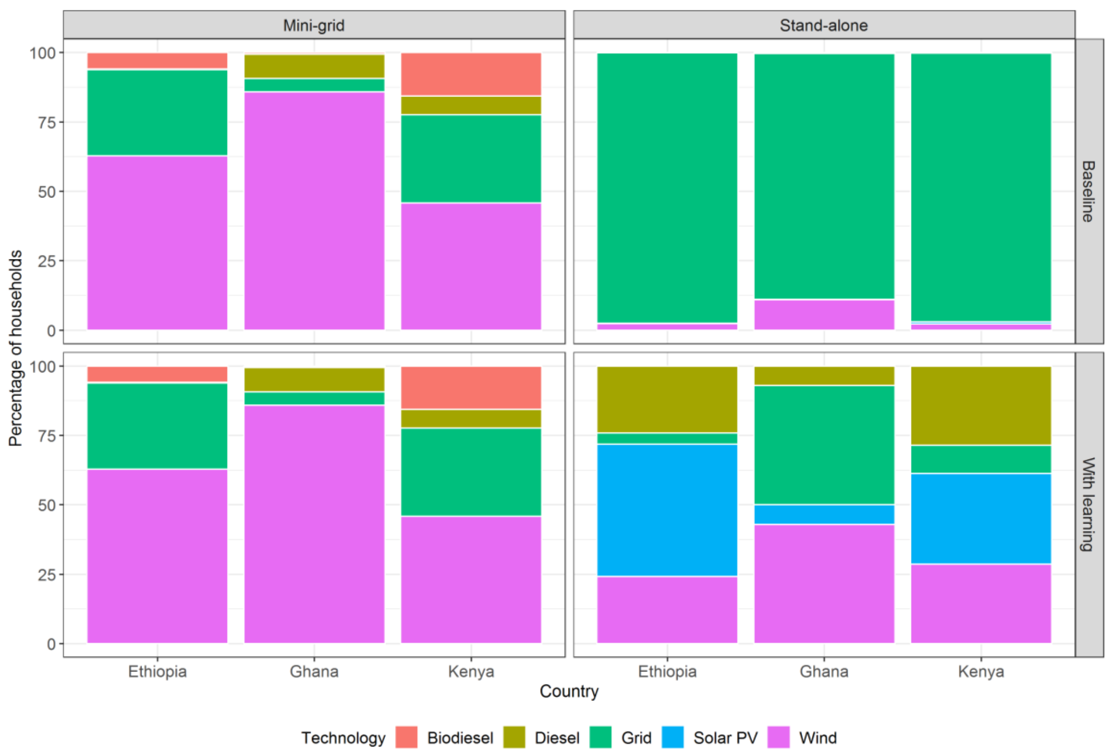
The model only compares mini-grids with stand-alone systems, generating lower LCOEs for mini-grids based on lower capital costs per kWh produced. Deichmann et al. does not appear to include information on how distribution costs were accounted for in mini-grids or whether they were excluded for stand-alone systems. The approach adopted in this model is not concerned with the

[54] The model actually bases this initial process on connecting existing generation infrastructure (though it ignores transmission infrastructure), where the number of generation points is fewer than the number of demand nodes. For details, see Deichmann et al. (2011).

extent to which demand is actually met by the system, and thus mini-grids produce lower prices than stand-alone systems across the board. No information could be gleaned from the model publication stating whether household demand profile was assessed, what level of reliability was assumed, or how batteries were sized (other than to note that storage costs were accounted for). The authors were contacted about this, but they did not respond.

Finally, the model considers how cost declines might affect the allocation of technologies by assessing historical learning rates for renewables and anticipated future demand over a 20-year period. Applying such cost declines results in a significant shift away from the grid when compared with stand-alone technologies, where wind and solar become much more prominent. Although learning results in cost reductions for mini-grids, it does not change the proportion of households served by different technologies; wind mini-grids continue to dominate. The results from Deichmann et al. (2011) are summarized in Figure A6.

Figure A6. Results from Deichmann et al. (2011): Least-cost technology allocation for Ethiopia, Ghana, and Kenya



Source: Derived from Deichmann et al. (2011).

There appears to be a conflict across the findings described in this publication. Within the body of the report, the report notes that wind mini-grids are competitive in Ethiopia, supplying 34 percent of households (p. 18). The full data, however, published in Appendix 2 (pp. 50–51) show that wind mini-grids are the cheapest source for every settlement in which wind is available. Summing these settlements reveals wind as the cheapest energy source for 62 percent of households (as shown in Figure A6). This is the only conflict between the findings discussed in the body of the report and the data published in appendix, and although the authors were contacted about this discrepancy, they have not responded.

Despite such contradictions, these findings are notable for the large role they ascribe to wind. This result is especially remarkable given that other models explicitly find a limited role for wind because it is located too far from most settlements to be useful. Again, the authors were contacted for an explanation, but no response was forthcoming.

Levin and Thomas (2012) seeks to model 150 countries around the world, with a specific focus on case studies in Bangladesh, Botswana, and Uganda, looking at the split between grid connections and distributed generation. This ambitious model is built around a set of algorithms that solve the computational problems regarding how to build electricity infrastructure. Like the Deichmann et al. (2011) model, this model does not look at the technology allocation for connecting the currently unconnected population, but rather models the whole country from scratch—i.e., assuming no grid infrastructure is in place. Again, this means that the model is likely to provide higher estimates for grid connections than does a model that considers only the unconnected population.

The model is based on an algorithm that seeks to connect settlements, with a focus on optimizing size and proximity—i.e., the densest and nearest settlements are connected first. This process is done until a set proportion of the country is connected to the grid. Next the model runs an algorithm that solves the minimum spanning tree problem to connect those selected settlements with the shortest possible distance (i.e., least amount of transmission infrastructure). The model works by running these two algorithms, increasing the percentage of people connected from 1 percent to 100 percent. As with Deichmann et al. (2011), this approach generates the cost for connecting any additional settlement (or the marginal cost for grid expansion). This marginal cost is compared with a cost per settlement of connecting each settlement using distributed generation sources for which, again, costs are estimated. In this instance, however, transmission costs are ignored.

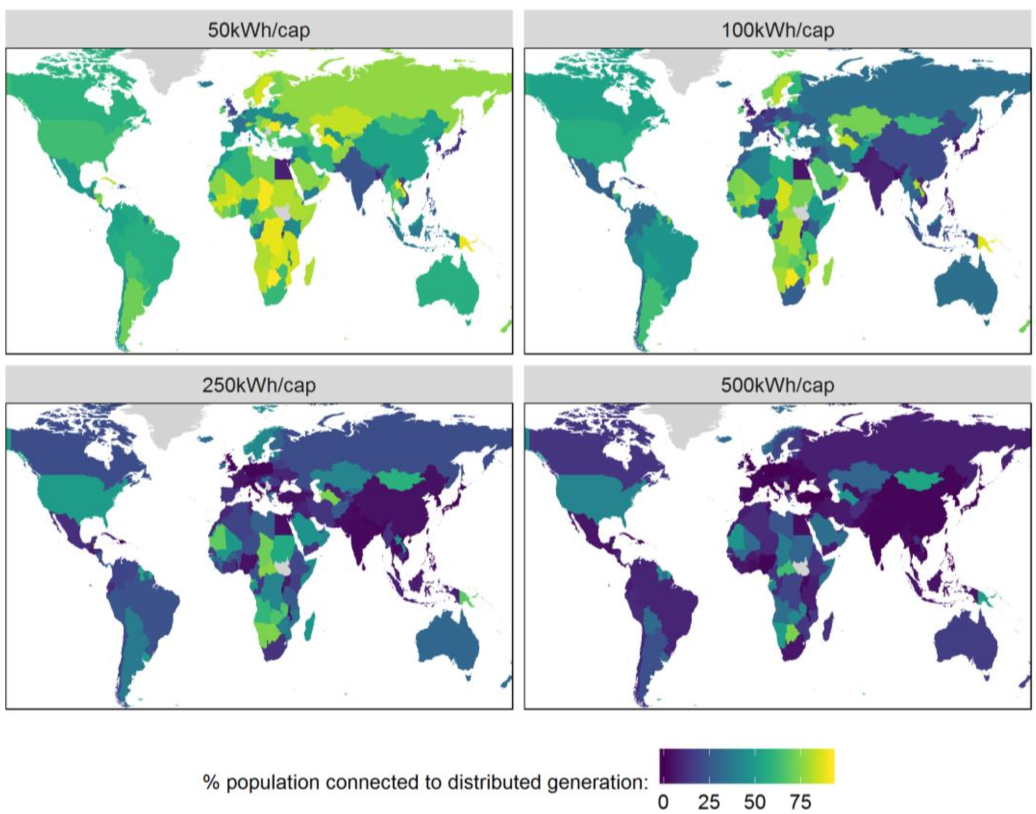
The model then compares the 100 percent grid-connected result with the distributed generation costs and removes grid connections for every case in which distributed generation costs are less than the marginal costs of grid connection. The model is thus left with an approximation of an optimal network, connecting only those settlements in which the marginal cost of connecting to the grid is less than distributed generation costs. From this calculation, the model derives an estimate of the split between on- and off-grid technologies.

The results show that, following a least-cost approach, distributed generation technologies would supply electricity to more than 50 percent of the population in 11 countries (Afghanistan, Central African Republic, Chad, Equatorial Guinea, Eritrea, Guinea-Bissau, Mali, Niger, Sierra Leone, Somalia, and Sudan). Furthermore, they identify 13 countries for which more than 90 percent of the population nodes can be electrified using distributed generation sources following a least-cost approach (Afghanistan, Central African Republic, Chad, Equatorial Guinea, Guinea-Bissau, Guyana, Mali, Mauritania, Mongolia, Niger, Sierra Leone, Somalia, and Sudan).

Despite the computational elegance of this model, its results are undermined by a number of factors. First, as mentioned, it ignores any existing grid infrastructure. Since other models show this existing infrastructure to be a major determinant of technology allocation, this is clearly a significant shortcoming. Second, demand is central to the model because it drives the cost of generation (entirely in the case of off-grid and partially in the case of on-grid). The model derives demand assuming the average demand of currently connected households. In cases where data are lacking, the authors estimate demand using regional averages. Both of these estimates are likely to overestimate demand because connected households are likely to use more energy and regions with data are likely to have more connected customers. Furthermore, the numbers used for this calculation seem troubling. Current demand is estimated by taking the total demand in the country and dividing it by the country's current rate of electrification, multiplied by the total population (data are from the IEA). The model says nothing about how domestic (as opposed to industrial) demand is estimated from this data. Reading the results of the analysis raises significant concerns that average domestic demand has been estimated using consumption figures that include industrial demand. For example, countries like Namibia (8,719 kWh per capita) and Guinea (10,321 kWh per capita) have extremely high demand (exceeding US per capita demand, according the US Energy Information Administration), thanks to their small populations and abundance of extractive industries. Indeed, the *per capita* numbers supplied for the United States by Levin and Thomas (2012) (12,365 kWh per capita) are equal to the *household* consumption provided by the US Energy Information Administration (10,666 kWh per household), suggesting that total consumption has been used and that industrial demand has been included in the model. This approach wildly overstates household demand. The authors were contacted about this decision but provided no response.

More usefully, Levin and Thomas (2012) also undertake their analysis considering a variety of levels of energy consumption, including 50, 100, 250, 500, 1,000, 2,500, 5,000, and 10, 000 (all kWh per capita per year). Because these scenarios are more useful than assuming the high levels of demand mentioned above, a quick mapping of a selection of these findings appears in Figure A7. Clearly low demand drives a greater allocation of distributed generation, with population density (or concentrations in the case of North Africa and the Middle East) being the primary driver of technology allocations. The limitations of the model—in that it assumes no existing grid—are clear by the way it characterizes countries with 100 percent grid access as having high percentages of off-grid access at low levels of demand. As a result, this model is really of value for indicating technology allocations only in countries with very limited grid extent and low levels of demand. Although these conditions apply to much of sub-Saharan Africa, grid extent varies significantly within this region, and thus results should be read with caution.

Figure A7. Results from Levin and Thomas (2012): Proportion of the population connected by distributed generation at selected levels of demand



Source: Visualization derived from data published in Levin and Thomas (2012).

Notable in these findings is the relatively large role for distributed generation, especially considering that the findings likely overstate the role for the grid. In addition, this analysis highlights the variable costs and input prices for the model. For transmission networks, for example, the paper points out that estimates range from $50,000 to $500,000 per kilometer. The model uses a cost for transmission infrastructure of $200,000 per kilometer. Similarly, the costs of supply from the grid are noted to vary significantly across countries, as are prices for distributed generation technologies. Despite talking about these variable costs, the paper does not make clear (as far as this reviewer can tell[55]) what cost is used for centralized generation or for distributed generation.

Van Ruijven, Schers, and van Vuuren (2012) undertakes an assessment of least-cost electrification technologies for Brazil, India, Indonesia, South Africa, and Eastern Africa (though the exact countries included in this last category are not stated).[56] The model starts by assessing the cost of electrifying 95 percent of the population in all countries. The model is built on top of a grid of $0.5° \times 0.5°$ cells, using data on population density and inhabited areas (the area within each cell that is considered inhabited). Correspondence with the paper's authors revealed that the location of existing grid infrastructure was taken from OpenStreetMap's infrastructure map. The location of currently connected households was then derived based on the national electrification rate and population density maps, assuming all existing connections occur via that grid. Based on this information, each cell was determined to be either electrified or not (A. Dagnachew, personal communication, August 31, 2018).

The model proceeds by connecting cells in order of increasing levelized cost. This process involves first determining the demand for the cell, based on an assessment of population and a predetermined level of household demand (the model runs scenarios for two levels of demand: 65 kWh per household per year and 420 kWh per household per year). The total demand in each cell determines the transmission requirements for each cell, as well as the requirement for the low-voltage networks. These networks are limited by either their capacity (in densely populated areas) or their length (in sparsely populated areas). Based on the length of the MV network and the number of households, the authors derive the length of the LV network. MV lines are served by HV lines, with two cells served by a single HV line, unless demand from these cells exceeds the capacity of that HV line. Transformer needs are estimated based on the number of junctures between high- and low-voltage lines. Finally, for each household additional charges are put in place to cover wiring and connection costs. As with

[55] The corresponding author on the piece was contacted about the numbers used in the model but did not respond.

[56] This study also includes the generation of an econometric model looking at the drivers of electrification globally. The authors' work shows that electrification in Africa takes place at higher levels of economic development (measured in terms of GDP per capita) than it does in Asia and Latin America. This work is not discussed in more detail here as it is not relevant to the content of this review.

other models, Van Ruijven, Schers, and van Vuuren (2012) considers only the cost of building new infrastructure, not of upgrading the existing grid.

Based on these calculations, the model looks at the cost of connecting an increasingly large proportion of the rural population. Since the model starts by connecting areas with the lowest levelized cost, as the share of the population that is electrified increases, the costs of electrification increase as well, reaching very high costs in some instances: $12,000 per household in the cases of Brazil and South Africa.

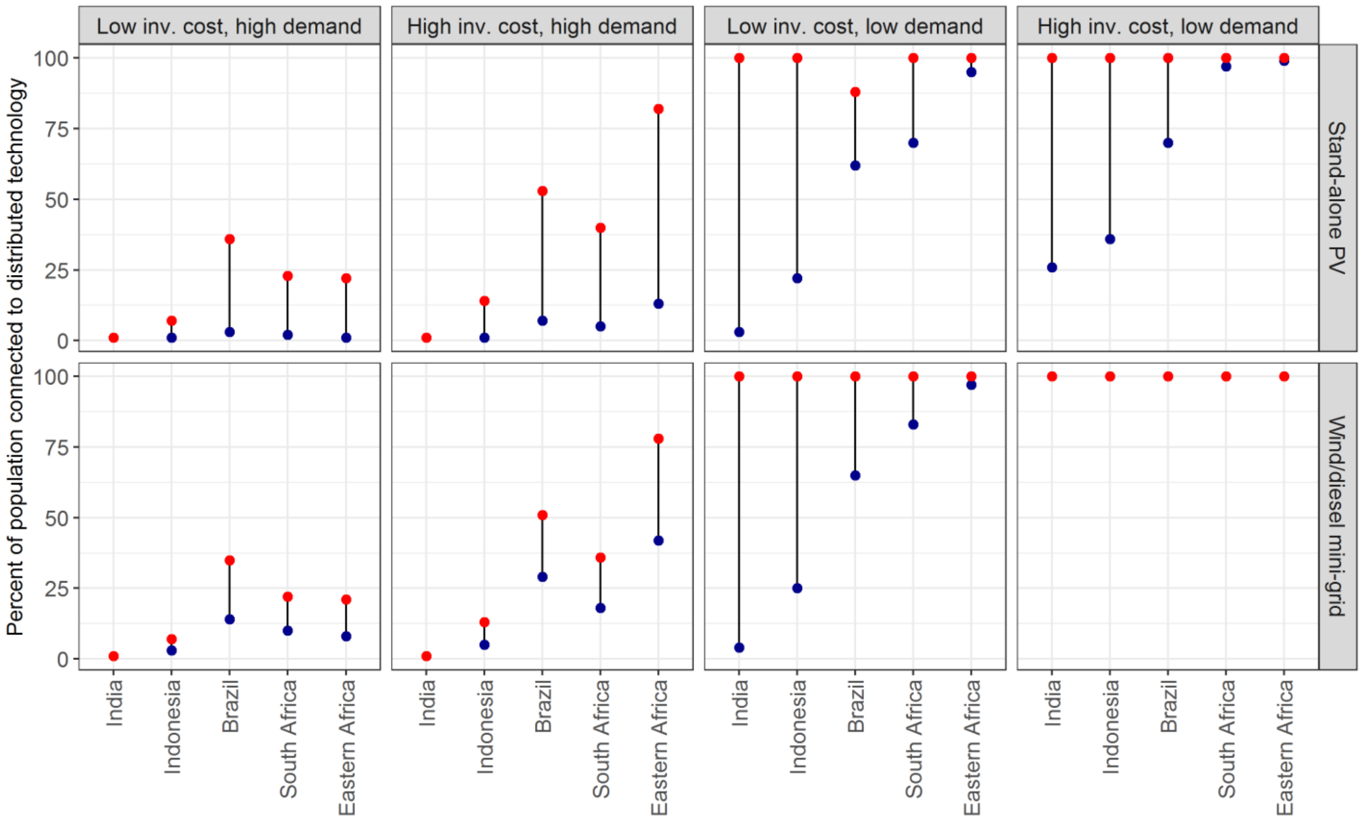
The model then seeks to assess what percentage of these households could be electrified by distributed renewables by looking at where the cost of distributed renewables drops below the cost of grid connections. To assess this, the model first adds $0.05 per kWh to existing grid costs to account for generation costs. In terms of distributed technology, it compares mini-grids and stand-alone PV. For mini-grids, the costs of wiring and distribution are the same as for the grid, with a generating cost added of $0.14–0.24 per kWh for local wind or diesel. For stand-alone PV, the household wiring costs are the same as for the grid, with generation costs set at between $0.35 and $1.2 per kWh.[57] The model does not consider the availability of wind resources or the increased cost of diesel as a result of distance to the nearest town. Nor does the report consider the point at which population pressure would make mini-grids competitive with stand-alone PV; instead it simply considers published levelized cost for mini-grids.

The model is run comparing scenarios assuming high and low investment costs,[58] and high (420 kWh per household per year) and low (65 kWh per household per year) levels of demand. The results show large variation across countries and scenarios (Figure A8). Where wind and diesel mini-grids have low generating costs, and where demand is low and infrastructure costs are high, the role for distributed renewables is thought to be extremely high. One notable finding is that assumptions about investment costs seem to matter more than assumptions about demand in driving the proportion of the population for whom distributed generation is cost competitive. This is an alarming finding given the large variance in investment costs for grid infrastructure that exist across the literature.

[57] This case illustrates the problems with how inputs are amassed for these models. Van Ruijven, Schers, and van Vuuren (2012) cite page 106 of a 2007 ESMAP report for these numbers. Consulting that report, however, reveals that it has only 68 pages. Personal communication with the authors identified the correct reference for wind and diesel prices, but the authors acknowledged that they were unable to identify the source for the PV costs used in the model (J. Schers, personal communication, August 28, 2018).

[58] High costs are as follows: HV lines ($78,000), MV lines ($9,000), LV lines ($5,000), metering and wiring ($250). Low costs are as follows: HV lines ($28,200), MV lines ($5,000), LV lines ($3,500), metering and wiring ($100)

Figure A8. Results from Van Ruijven, Schers, and van Vuuren (2012)



Source: Visualization derived from data in Van Ruijven, Schers, and van Vuuren (2012).
Note: Blue dots indicate high generation prices, and red dots indicate low generation prices.

Dagnachew et al. (2017) builds on the model developed by Van Ruijven, Schers, and van Vuuren (2012). They update the model to consider rural and urban electrification as well as a host of distributed generation technologies, including both stand-alone (PV and diesel) and mini-grids (PV, diesel, wind, micro-hydro, and hybrid). This time, however, the model is applied only to sub-Saharan Africa, and it assesses technology allocation to 2030 considering a number of scenarios that vary in terms of both level of household demand and target electrification rate. The model is notable for invoking multiple time steps from 2010 to 2030, updating technology allocations every year (A. Dagnachew, personal communication, August 31, 2018).

The model is again built on top of a $0.5° \times 0.5°$ grid, using the OpenStreetMap infrastructure database to determine the location of the existing grid and the LandScan data set to locate population density for each cell in the grid. To determine the location of currently connected customers, the model uses the same approach as Mentis et al. (2015, 2016) in drawing a corridor around the existing grid and expanding that corridor until it covers the proportion of the population equaling the electrification rate.

The authors do not describe the order of calculations undertaken by the model but rather the decision tree by which technologies are assigned. They describe three steps: First, grid generation costs are compared with distributed generation costs, and the cheapest cost is assigned to the cell. Second, in an approach similar to that of the Network Planner model, the distance between the cell and the grid is calculated, and a cost for extending the grid to that cell is calculated based on an assumption about grid extension costs (provided in $/km). If the generation cost plus the extension cost remains below the difference in generation cost between the grid and the distributed technologies (for a set level of demand), then the grid is selected as the technology to connect the cell; otherwise the cell is connected by distributed generation. Third, the model has to select between stand-alone distributed generation and mini-grids. This decision is made based on standard numbers for mini-grid calculations undertaken elsewhere. The decision involves checking whether the cell meets threshold levels for at least two of the following three conditions: population density of the cell (derived from Fuso Nerini et al. 2016; see below for a discussion), electricity demand per household, and the distance of the cell from the existing grid. The last of these is intended to account for the fact that subsequent grid expansion can jeopardize the financial viability of mini-grids (see Morrissey 2017 for more details on this process).

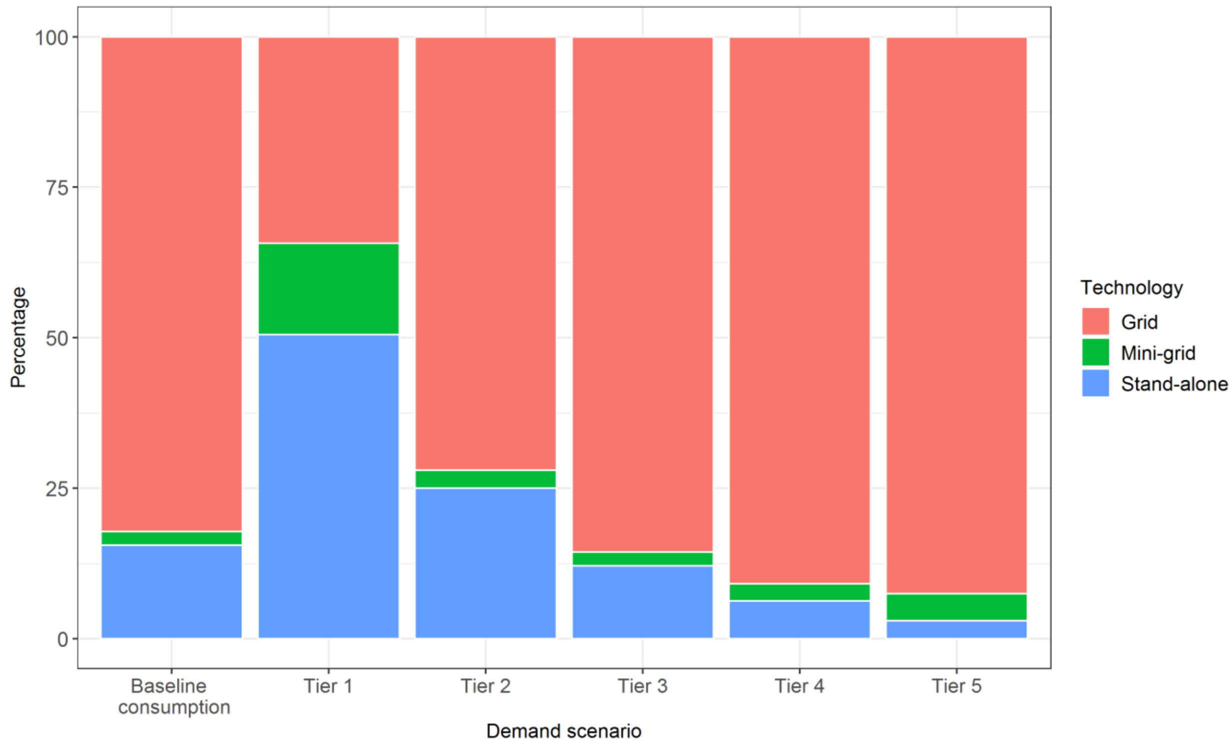
Because the model incorporates multiple time steps, it can consider the impact of declining renewable prices through to 2030 by applying a learning rate derived from Stehfest et al. (2014). This results in per-kilowatt-hour prices for distributed generation as low as $0.09 for solar PV mini-grid, $0.11 for wind, $0.14 for mini-hydro, $0.16 for PV-diesel hybrids, and $0.15 for wind-diesel hybrids by 2030.

For mini-grids the model does not consider demand profiles but simply sizes the system to meet peak demand, with a battery capacity to provide autonomy for one day at 50 percent discharge. Hydro potential was evaluated for every 10 km on rivers with a discharge of less than 50 cubic meters per second. Potential reservoir capacity was determined by Hydro SHEDS topographic data with costs derived from equations developed for US and Norwegian hydropower tenders (Dagnachew et al. 2017).

The model first considers a baseline scenario, which is the expected rate of electrification and average demand achieved in sub-Saharan Africa if no new policies are implemented to drive energy access. This assessment is based on the econometric model developed by Van Ruijven, Schers, and van Vuuren (2012), mentioned briefly above. Under that model the electrification rate is a little over 60 percent (total population in 2030 is about 1.3 billion) with average demand at between tiers 3 and 4 in the World Bank Multi-Tier Framework for measuring energy access. Then the model considers the universal access scenarios, which vary by demand, to consider the demand from the baseline scenario and tiers 1–5 of the Multi-Tier Framework (the model uses the lowest demand level for each tier). Model results, shown in Figure A9, were obtained from personal communication with Anteneh Dagnachew (September 1, 2018).[59]

[59] Dagnachew (personal communication, September 1, 2018) provides only graphical representations of the results, not tabulated data, and the images published there show the technology shares for all connected populations, including already connected populations. In contrast, Figure A9 refers specifically to the newly connected population. The tabulated data that inform this figure are from personal communication with Dagnachew (September 1, 2018).

Figure A9. Results from Dagnachew et al. (2017): Percentage of newly connected population by technology, across multiple demand scenarios



Source: Visualization derived from personal communication with Anteneh Dagnachew (September 1, 2018).

The model findings show that grid connections come to dominate the proportion of newly connected households at all demand levels above tier 1. The proportion of investment costs follows this same pattern. This finding is notable because (1) in other models the grid dominates only at tier 3 and higher, (2) this pattern occurs even though the model achieves low LCOE numbers for distributed generation by 2030 based on the application of a learning rate, and (3) mini-grids play a small role in all scenarios.

Finally, the model undertakes sensitivity testing, varying the costs of diesel and grid investment. Varying the diesel price has little impact (though the range used is on the low side—$0.5–$0.8 per liter—whereas many models assume a diesel price of $1 a liter before transport costs). Varying grid investment costs has a significant impact, though this impact is mitigated by the level of demand in each case. At low levels of demand, high grid costs result in an additional 110 million people gaining access through distributed systems. At high levels of demand, the number drops to 20 million (see Table 2 for grid costs).

The model has several limitations. It treats every cell individually and therefore cannot appreciate that technologies might be viable owing to scale achieved across cells. In addition, it treats demand as constant and fails to consider that demand would vary across households over time (increasing with time connected) both within and across rural and urban areas.

Bertheau, Cader, and Blechinger (2016) considers the electrification pathway in Nigeria. The model draws upon population data sets augmented with polling places and schools (both of which are thought to have populations around them). Based on these data, the country is broken down into spatially defined clusters of potential consumers. Data on the extent of the grid in Nigeria are too poor to include in the model, and thus the electrification status of each cluster is determined using nighttime imagery augmented with data on the electrification status of schools; all areas with light or with an electrified school are considered electrified. All areas within 20 km of any electrified cluster are assumed to be serviced most cheaply with a grid connection. Outside of this buffer zone, all clusters with populations of fewer than 1,000 people are assumed to receive stand-alone systems, while all the remaining clusters are electrified using mini-grids. Results appear in Table A11.

Table A11. Results from Bertheau, Cader, and Blechinger (2016)

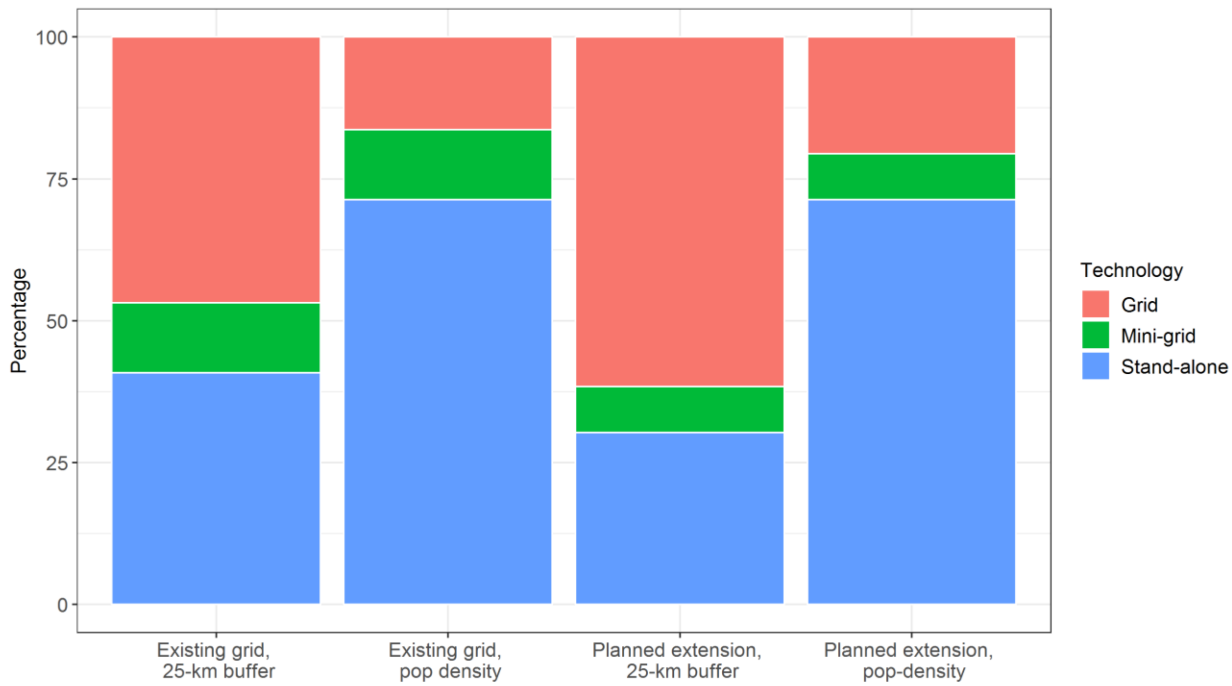
Indicator	Grid	Mini-grid	Stand-alone PV
Number of people connected to technology	57.1 million	12.8 million	2.8 million
% of connections	78.5	17.6	3.9

As expected, in more remote and sparsely populated states, distributed delivery systems play a larger role. The authors conclude that although the grid dominates as the cheapest form for delivering electricity, distributed systems still play a significant role.

Bertheau et al. (2017) models the least-cost electrification pathway for all of sub-Saharan Africa. The model first identifies all households that lack electricity by triangulating assessments of nighttime light emissions and population density with IEA numbers on electrification rates. It then draws a 25-km buffer around the existing grid infrastructure and assumes that everyone within this buffer is connected most cheaply to the grid. Data on the location of grid infrastructure were based principally on the AfDB and UN DESA data sets on transmission infrastructure. In countries where data were missing, the authors requested information directly from country ministries and agencies; nonetheless, country data were still incomplete. For those outside of the grid buffer, the model sets a population density threshold for receiving either mini-grid systems (more than 400 people per km^2) or stand-alone systems (fewer than 400 people per km^2). It sets this threshold based on other literature, citing Fuso Nerini et al. (2016). The authors test the model so that areas within the 25-km zone buffering the grid must also meet the 400-people-per-km^2 threshold to receive a grid connection.

They run two instances of the model: one that focuses only on the existing grid and one that considers any existing planned grid extensions, usually intended to connect mines and new generating plants. The results show a large role for stand-alone systems (at lowest 30 percent) and a relatively small role for mini-grids (Figure A10), which the authors point out contradicts the IEA (2017) analysis.

Figure A10. Results from Bertheau et al. (2017)



Source: Visualization derived from data published in Bertheau et al. (2017).

The model then considers the impacts of replacing the assumption that everyone within a 25-km buffer of the grid gets connected to the grid with a requirement that, even within the 25-km buffer, population density must exceed 400 people per km^2 in order to receive a grid connection. Doing so changes the outcomes of the model quite dramatically (see Figure A10).

Bertheau et al. (2017) undertakes sensitivity tests against a baseline model (using the existing grid), changing the size of the buffer zone (to 10 km and 50 km) and the threshold for mini-grid/grid connection and stand-alone system (to 100 people per km^2). While changing these parameters changes the outcomes of the model, the overall picture remains the same, suggesting a relatively small role for mini-grids. The most sensitive parameter is the population threshold for allocating mini-grids: lowering it to 100 people per km^2, results in a shift away from stand-alone (–24.6 percent) toward the grid (+15.6 percent) and mini-grids

(+9 percent). Such a sensitivity test effectively tests whether demand might have been underestimated.

Sahai (2013) models the least-cost technology allocation for achieving 100 percent electricity access on Flores Island, Indonesia, which has a population of more than 1 million people and an electrification rate of 40 percent (170,000 electricity connections). The model compares grid connections, solar mini-grids, and stand-alone solar home systems. It begins by using census data to determine the number of people in unelectrified households in each village administration (*desa*). It then uses geospatial data on the existing grid to determine which areas of the *desa* are actually inhabited (linking population and land-use data). By consulting geospatial data on MV power infrastructure, the model identifies the location of unconnected households and their distance to the nearest grid source.

The model notes that results are essentially driven by the number of households (i.e., population density). For settlements of fewer than 10 households, solar home systems are cheapest, whereas for settlements of more than 1,000 households, grid connections are cheapest. Mini-grids work in settlements of 11–50 households and are viable for 20 percent of settlements of between 50–250 households. Specific results appear in Table A12.

Table A12. Results from Sahai (2013)

Indicator	Grid	Solar mini-grid	Solar home system
Number of connections	166,000	84,400	2,650
% of connections	65.60	33.35	1.05
Cost ($ millions)	168	94	5
% of cost	62.92	35.21	1.87
Cost/connection ($)	1,012.05	1,113.74	1,886.79

Zeyringer et al. (2015) models the least-cost technology allocation for electrifying Kenya, comparing grid extension with stand-alone PV.[60] The authors undertake an extensive effort to estimate latent demand for electricity, building an econometric model to do so. This model is based on an assessment of household demand among existing households, controlling for factors such as income, age and education of the household head, size, and urban or rural designation. The authors consider only households within 100 km of the grid, ignoring data from Nairobi and Mombasa, which are likely to be too different to be useful. Based on this analysis, they estimate demand at between 164 and 1,880 kWh per household per year.

[60] The authors made this limited assessment because they lacked data on regional diesel prices and on wind and micro-hydro generation.

They then build the electrification model on top of a grid of cell, each 2,000 km^2 in size. The model operates by determining the cost of connecting each cell based on an assessment of demand. The cost of grid generation is set at $0.13 per kWh, transmission cost is set at $157,470 per km (based on consultations with the Kenyan Power and Lighting Company), and distribution charges are determined based on a rate of $0.1027 per kWh, where a 1 percent increase in population leads to a 6 percent increase in distribution costs. For stand-alone PV systems, costs varied by cell based on solar radiation availability, and the average cost is estimated at $0.56 per kWh.[61] The publication provides no information on how batteries are sized or on the expected lifetime of the solar components. The model does not make clear how grid construction is optimized to minimize the distance between cells. Furthermore, the model does not make clear the source used for determining current grid location. The author was contacted about these issues, but no information could obtained as the author was on maternity leave (S. Pachuri, personal communication, August 29, 2018).

The model considers a 2005/2006 baseline scenario (which essentially uses grid, PV, and battery prices from that period) and a 2020 scenario. For the 2020 scenario, prices for PV are projected based on estimates from the IEA and IRENA. Estimates for battery prices are hard to come by and thus left the same as in the baseline scenario. Grid prices are assumed to stabilize at $0.17 per kWh in 2018, based on projections from the Kenyan Ministry of Energy.

The results of the analysis show that in 2005/2006, stand-alone PV is the cheapest option for 80 percent of grid cells in Kenya (Figure A11). However, this large share accounts for only 22 percent of households because these cells are sparsely populated. For the 2020 scenario, changes in the inputs (lower PV costs; increased grid generation costs; and increased demand due to increased income, education, and population growth) cancel each other out so the proportions remain almost the same. If, however, only electricity demand is increased and all other parameters remain constant, 6 more cells receive a grid connection so that only 17 percent of households and 78 percent of cells receive stand-alone PV.

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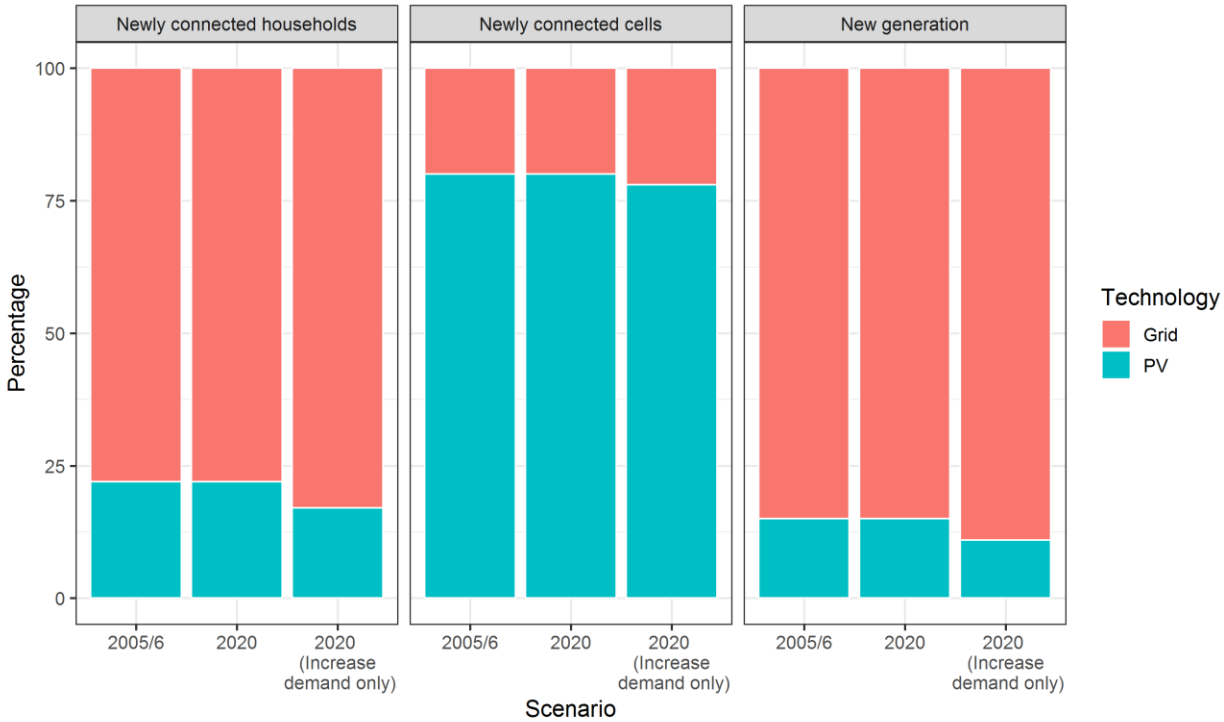
[61] The authors do not provide this figure, so it has been calculated here. This is based on the following original data: solar installation costs of $250/$m^2$, battery costs of $4.17/W, additional component costs of $100/$m^2$, solar efficiency of 12 percent, average solar irradiation of 2,007 kWh/m^2, and a discount rate of 6 percent. Although not stated in the work, this analysis assumes that each household requires a 60 watt battery. Batteries are replaced every 4 years while the rest of the solar components last 20 years.

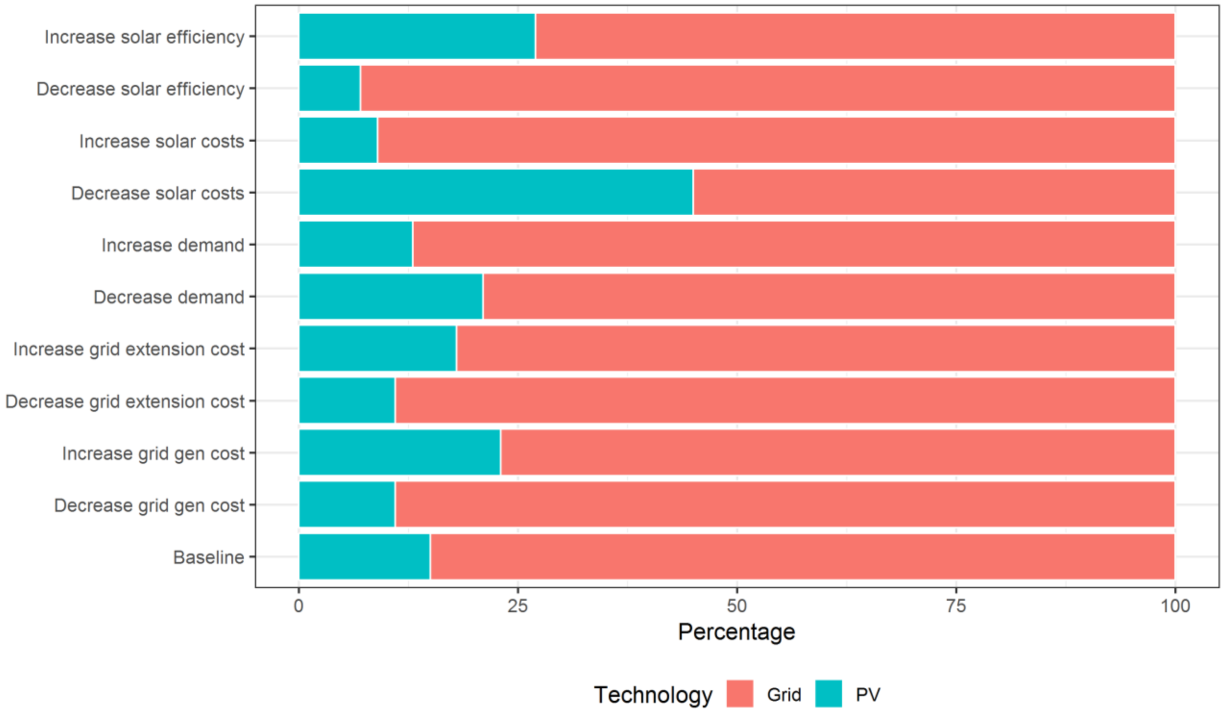
Figure A11. Results from Zeyringer et al. (2015)



Source: Visualization derived from data published in Zeyringer et al. (2015).

Zeyringer et al. (2015) further undertakes sensitivity analysis in which the authors increase and decrease the following factors by 50 percent: solar efficiency, solar costs, demand, grid extension costs, and grid generation costs. They then consider the impact on overall generation. From this analysis, it is clear that the greatest sensitivity is to decreasing solar costs, which drives PV generation to 45 percent, and increasing solar efficiency, which pushes PV generation to 27 percent (Figure A12). Overall, however, the results are notable for confirming the relatively dominant role of the grid in electrifying Kenya.

Figure A12. Sensitivity analysis from Zeyringer et al. (2015)



Note: For all scenarios, increases and decreases are by 50 percent.
Source: Visualization derived from data published in Zeyringer et al. (2015).

The model's limitations include its limited grid resolution (2,000 km^2) and its failure to consider any planned grid development or other distributed generation sources (hydropower, biomass, and wind). Furthermore, it fails to consider how access affects demand and how demand might change over time.

Ellman (2015) models the least-cost allocation of technologies to achieve universal energy access in the Vaishali district of Bihar, India. Ellman (2015) uses the Reference Electrification Model, developed by MIT, to consider the allocation of PV, diesel, and grid connections. The model, like others used here, is a single-time-step (or overnight build) model. It is computationally intense but provides a great deal of detail. For this reason, only the relatively small area of Vaishali (population: 3.5 million) is modeled. The area has an electrification rate of 16 percent and a very high population density of 1,700 people per km^2—despite being 93 percent rural.[62]

The location of existing grid infrastructure is derived from a map that describes all of the district's infrastructure,[63] augmented with consultations with the chief

[62] This is more than three times the population density of New Jersey, the most densely populated US state.

[63] The identification of this map is what drove the choice of field site.

engineer responsible for the grid in this area. The model attempts to identify the unelectrified structures, creating a digitized map of every structure that will be electrified (street lights, houses, hospitals, etc.) in the area, based on Google Images photos. This process is then augmented with census data. Unelectrified households are identified by looking at the location of MV power lines and assuming that the electrified population resides within a corridor surrounding that infrastructure. Demand data are based on the assumption that newly connected households will consume like average rural households—though the author notes that if reliability is improved, demand would likely increase. Demand data is estimated from the current demand on medium-voltage nodes. The model increases demand over time and accounts for variable peak demand across households.

The model uses a standard diesel price of $1 per liter. Battery costs, labor costs, and parts for PV systems are all derived from locally relevant studies and sources. The model assumes three-phase power for the grid. Based on consultations with the utility, the author determines the cost of supply as $0.1 per kWh for existing customers. To account for the increased cost of servicing new customers, Ellman sets the cost at $0.2 per kWh.

A principal difference between this model and others is the effort to cluster customers into potential mini-grids. This clustering occurs because the model uses individual households rather than simply selecting a technology for an entire population node or cell. The exact method used to achieve this cannot be discussed in its entirety here, but it drives significant differences in results (see below).

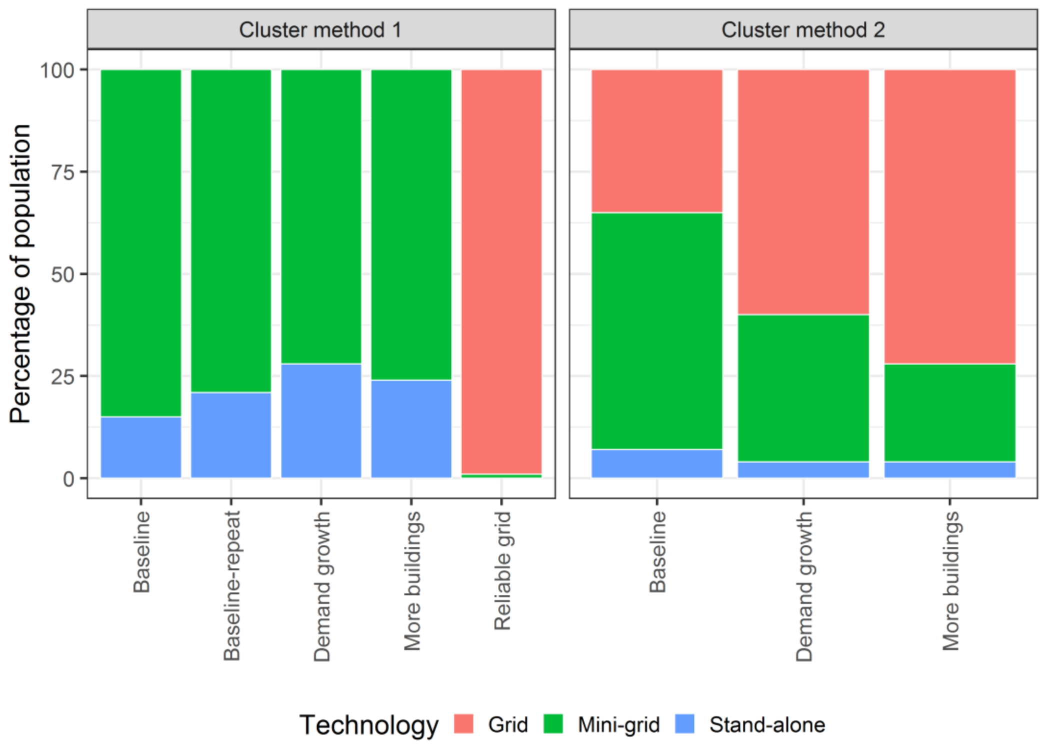
Also notable is that the model costs non-serviced demand. It achieves this by accounting for both critical and noncritical demand and then optimizing systems to allow for not meeting noncritical demand. This approach allows for distributed systems to be optimized and means that the cost of the current grid unreliability is accounted for. The value of unmet demand is set at between $1.5 per kWh and $2 per kWh. To assess the grid's current capacity to meet demand, current grid reliability was estimated from logbooks stored in the transformers. The author notes that this information was of limited accuracy because (1) the study looked at MV lines whereas LV lines could have worse performance, (2) the logbooks ignore seasonal changes, and (3) the study looked at relatively centralized transformers but more remote lines could have worse service.

The model then works out the cost of meeting demand for every customer with a stand-alone solar system. It undertakes the clustering process to check the potential for mini-grid formation and reallocates structures to a mini-grid in every case where a mini-grid is cheaper. The model looks at the cost of connecting mini-grid clusters to the grid, accounting for generation and transmission costs.

The author notes that this model is imperfect because it focuses on extending MV lines and does not account for extending existing HV or LV lines.

The model produces a baseline result in which: i) the number of customers matches the data on the current population in Vaishali, ii) experiences 1% demand growth annually, iii) assumes current grid reliability and iv) compares gird extension and microgrid development. The models repeats the baseline to check robustness of results. The model additionally runs the following scenarios: perfect grid reliability, 16 percent annual increase in demand, and 13 percent annual customer growth (driven by more buildings) on top of the existing population. These scenarios are tested across two clustering approaches.

Figure A13. Results from Ellman (2015)



Source: Visualization derived from data published in Ellman (2015).

Under the first cluster method, the baseline model is run twice to ensure it gives similar outputs (Figure A13). The baseline and two demand growth scenarios are tested across two clustering approaches. Three notable findings stand out from the results. First, mini-grids play a substantial role in almost all cases. Large PV-diesel mini-grids are able to get prices down to about $0.3 per kWh. In addition, although not shown in the figure, the paper reports that small PV-battery systems play an important role. Second, the grid's lack of competitiveness is due to its unreliability, which, when costed as it is in this model, limits grid expansion. When, however, the grid is assumed to be reliable (though the costs of achieving this are not included), it is the cheapest option for 99 percent of structures. Finally, as mentioned earlier, the clustering approach matters enormously. This difference in results is driven by the fact that one clustering approach places households in lots of small clusters that lack the scale to justify grid connection. The other approach creates large clusters and therefore affords greater opportunities for realizing the scales necessary to warrant the grid. No other model described here even engages with this issue, yet it clearly has significant impacts. The extent to which these results are applicable only to densely populated areas is unclear and deserves future study.

Finally, this appendix includes a summary of work by **Fuso Nerini et al. (2016)**, which informs the methods and estimates used in various models mentioned here (Mentis et al. 2017, 2016, 2015; Moksnes et al. 2017; Dagnachew et al. 2017; Bertheau et al. 2017). Fuso Nerini et al. (2016) do not build an LCEM for an actual location but rather calculate the LCOE for a number of different technologies (grid, diesel generator mini-grid, PV mini-grid, hydro mini-grid, biogas mini-grid, PV stand-alone, diesel generator stand-alone) as well as the total cost per household of meeting energy needs. They do this for different levels of demand and different levels of population density located at different distances from the grid.

The model uses broad categories of resource availability and fuel cost: Solar radiation is high (2,000–2,500 kWh per square meter per year) or medium (1500–2000 kWh per square meter per year); wind capacity factors span 20 to 40 percent; mini-hydro either is available within 10 km from the demand center or is not; diesel costs are assumed at values of between \$0.5 and \$1 per liter for mini-grids and between \$1 and \$2 per liter for stand-alone generators. The model considers electricity prices ranging from \$0.05 per kWh to \$0.4 per kWh. It is worth noting up front that capital costs in Fuso Nerini et al. (2016) do not capture the steep cost declines in renewable components that have taken place since the article was published (F. Fuso Nerini, personal communication, March 13, 2018). The model's findings are thus likely to be conservative in terms of the role for distributed renewable technologies. The work's own sensitivity analysis (which decreased renewable component costs by 20 percent) showed that this would likely result in a larger role for distributed PV compared with distributed diesel. The overall findings are as follows:

- For tier 1 energy access (22 kWh per household per year), stand-alone systems provide the cheapest electricity across all population densities and at any distance from the grid.
- For tier 2 energy access (224 kWh per household per year):

        - At low population densities (100 households per km^2), mini-grids provide the cheapest energy access regardless of distance from the grid.
        - At high population densities (500 households per km^2):
            - Households within 10 km of the grid are served most cheaply by the grid, unless they have access to micro-hydro.
            - At 20 km from the grid, grid connections and stand-alone systems are largely comparable.
            - Grid connections are not competitive at 30 km from the grid.
    - For tier 3 energy access (695 kWh per household per year):
        - At low population densities, micro-hydro is cheapest; otherwise grid connections and mini-grids are comparable as the cheapest energy source.
        - At high population densities, micro-hydro is cheapest; otherwise the grid is cheapest up to 20 km from the grid. At 30 km from the grid, mini-grids become competitive.
    - For tier 4 and 5 energy access (greater than 1,800 kWh per household per year), micro-hydro is cheapest wherever it is available. Otherwise, the grid is cheaper up to 30 km from the existing grid.

Fuso Nerini et al. (2016) also apply their general model to the specific cases of Ethiopia and Nigeria. Because these results are discussed by Mentis et al. (2015, 2016), they are not repeated here.

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