Integrating Medium-Voltage Lines into the OnSSET Model for Electrification Planning

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4/26/2019

Masters project submitted in partial fulfillment of the

requirements for the Master of Environmental Management degree in

the Nicholas School of the Environment of

Duke University

Executive Summary

Policymakers working to extend electricity to the one billion people living without access struggle to identify the least-cost pathways for these overwhelmingly rural populations. Least-cost electrification pathways can be difficult to identify as they depend on geospatial, social, economic, technical, and other factors. Planners operating with limited budgets must weigh competing grid and off-grid electrification technologies with multi-decade planning horizons.

A class of electricity access modeling tools helps fill this information need for planners by identifying least-cost grid and off-grid technologies to electrify whole study regions. This Master's Project focuses on the OnSSET model, a leading example of this class of "techno economic" (TE) models developed by KTH Royal Institute of Technology. OnSSET is currently being developed and deployed in the field.

Concurrent with the maturation of TE models, new classes of geospatial energy data are beginning to emerge from burgeoning machine learning techniques coupled with high-resolution aerial imagery. These new data promise to unlock additional features and insight potential from TE models, but in doing so, raise their own questions: what additional insight can this data bring and how should it be integrated into existing TE models?

This Master's Project examines how new, previously non-existent data on Medium-Voltage (MV) electricity infrastructure should be integrated into the OnSSET model. MV infrastructure - i.e. towers and lines carrying electricity between 1 and 69 kV - falls in-between transmission and distribution infrastructure in terms of the energy capacity it can transport. Neither MV nor Low-Voltage distribution data is currently usable by the OnSSET model since it historically has not been widely available. OnSSET uses more accessible High-Voltage (HV) infrastructure data to estimate electricity status (i.e. who currently has access) along with the cost of extending grid power to unelectrified communities. This work proposes that MV infrastructure be employed by OnSSET for similar goals, requiring adjustments to OnSSET's parameters and methods to account for the lower cost and capacity limits inherent with MV infrastructure. To evaluate the impacts of changes to the OnSSET model, I employed a case study using data for the whole country of Afghanistan.

My major contributions fall into two categories. I adjusted the core OnSSET model to facilitate MV integration and created a stand-alone algorithm to study possible approaches for optimizing grid-extension using MV infrastructure with capacity limits. Complications can arise when comparing grid and off-grid power technologies as a result of their differing dispatchability. Grid power generated with conventional thermal power plants can be dispatched at any hour whereas solar off-grid technologies can only be dispatched at night in the absence of a storage solution. The core OnSSET model gives off-grid solar technology unrealistically low dispatchability requirements in the absence of a secondary technology, so I increased costs for off-grid solar to be more realistic. This significantly increased the cost of off-grid power, pushing recommendations for a large percentage of the population from solar to grid and other off-grid technologies. Similarly, the core model costs for HV grid extension hardware and interconnection were unrealistically low when compared to real-world costs. Upon

increasing this cost, HV grid extension became less competitive with the new class of MV grid-extension.

Since I did not have real data for the locations of MV infrastructure in Afghanistan, I identified which communities would be ideal targets for this new technology and over what distance they could afford to extend the MV grid. I found that about 5% of communities or “cells”, representing about 30% of the total country’s population, would benefit from MV grid-extension versus their current off-grid technology recommendations. The biggest determinate for the feasibility of MV-extension and the distance the cell could afford to extend the MV grid was its population. Larger cells can afford larger fixed-cost investments, resulting in lower marginal costs for delivered electricity. Feasible cells tended to be located near population centers in Afghanistan, near existing or planned HV grid-expansion, suggesting that the communities that could most benefit economically from MV grid-extension are near where it likely lies.

Since MV grid-extension should be carried out with capacity constraints, I designed an algorithm to prioritize MV-extension to maximize annual savings while remaining within peak capacity limits. When tested in a randomly assigned selection of feasible cells, this algorithm chose to electrify the largest cells since they saved more money annually than smaller feasible cells. If electrification planners want to maximize savings with their MV grid-extension, they would choose a less orderly extension approach, stretching significantly farther distances (even bypassing smaller but less profitable cells) to reach larger cells. This extension approach has potential risks. Besides being unfair to people in smaller communities, it may pose a challenge to electrification efforts by requiring longer distances of extension versus less profitable, shorter grid extensions. Alternatively, electrifying larger communities first results in fewer communities being electrified, potentially simplifying deployment efforts.

Results from my core model updates as well as my experimental grid-extension algorithm suggest that adding MV infrastructure to OnSSET would likely result in predictable and useful outcomes. The challenges that arise from introducing a class of grid extension with capacity constraints would certainly complicate the OnSSET model and result in a longer run-time, but I believe they are worthwhile and necessary to giving electrification planners the best possible information. The team at KTH developing OnSSET has been interested in including MV data in an upcoming release, and I hope that this work both provides insight and inspiration for the practical implications of including this new data.

1. Introduction

Extending electricity access to the 1 billion people worldwide who live without is a complex and costly undertaking, requiring data-driven methods to inform decision makers. Models for electricity access optimization fill this role by leveraging geospatial data to determine the least cost grid and off-grid electrification options for a region of study. The emergence of modern machine learning techniques coupled with abundant satellite imagery promises to provide a new source of transmission and distribution infrastructure data for electricity access modeling, yet questions persist about how to best integrate this new data into existing models. My work focused on the popular OnSSET model for electrification planning, and I explored updating the model to accommodate new data on the location of Medium-Voltage (MV) transmission infrastructure (KTH n.d.). In addition to adjusting the core model to incorporate this new class of input data, I built an add-on to optimize grid-extension from MV interconnections. Applying this updated model to a case study in Afghanistan, I found small parameter changes can have large impacts on the electricity planning pathways for a region. Similarly, the inclusion of MV infrastructure has great implications for the feasibility of grid extension.

1.1 Development and Energy Access

Lack of electricity access has dire implications for communities, affecting an estimated one billion people worldwide, mostly located in rural sub-Saharan Africa and South Asia (UN 2018). Development appears to be tightly linked with electricity access, suggesting a widening poverty gap between those in the developing world that have access and those that do not (World Bank 2018). The United Nations identified the urgency of closing this gap for the world’s least developed countries, including access to affordable and clean energy as one of its seventeen Sustainable Development Goals for 2030 (Sustainable Development Knowledge Platform 2018).

1.2 Electricity Access Planning with Geospatial Data

Extending electricity access to the millions who currently live without is complex, costly, and requires large-scale planning and optimization to allocate limited resources. The challenge has a unique geospatial component too, since distances - from roads, existing grid infrastructure, and other salient features - impact the suitability of different on- and off-grid electrification options. Similarly, other geospatial factors, such as solar and wind resources, topography, and population density, determine the comparative economic viability of different technologies for each locality. As a result, models for electrification planning often include geospatial data along with economic and social parameters for their region of study (Howells et al. 2017).

The development of geospatial tools for modeling energy access in the developing world is a relatively young field and tools embody a variety of end-goals. One study identified six dimensions under which to evaluate existing tools based on their pursuance of United Nations Sustainable Development Goals (SDG) surrounding energy access: Political, Economic, Social, Technological, Legal, and Environmental (Moner-Girona et al. 2018). This Master's Project will focus on the Open Source Spatial Electrification Tool (OnSSET), one such tool for modeling the Technological and Economic dimensions of electricity access (Moner-Girona et al. 2018).

OnSSET, a "techno-economic" electrification planning toolkit developed by the division of Energy Systems Analysis at KTH Royal Institute of Technology (OpeN Source Spatial Electrification Toolkit 2017), calculates least-cost electricity access options for every point in a region based on technological feasibility and economic costs, both stemming from geospatial data and other locale-specific parameters. It was developed to strike a balance between usability and the scarcity of underlying data, incorporating only publicly available and relatively-abundant inputs.

1.3 Energy Infrastructure Data in the Developing World

Low-Voltage (LV) power lines typically support voltages lower than 1 kV, Medium-Voltage (MV) lines support between 1 and 69 kV, and High-Voltage (HV) lines support higher voltages. Power line capacity (measured in kilowatts or megawatts) increases with voltage levels.

To illustrate the relatively scarcity of geospatial data on distribution (LV and MV) infrastructure, I refer to energydata.info, a leading repository for electricity access planning datasets (ENERGYDATA.INFO n.d.). Out of 50 developing countries listed with T&D data on energydata.info, only 8 countries have data for "distribution" or "Medium-Voltage" infrastructure, 6 of which are included in a dataset released in early 2019 from a collaborative effort between KTH and Facebook (Predictive model for accurate electrical grid mapping 2019).

OnSSET's design decision to only incorporate maps of HV infrastructure, born from a dearth of data on LV and MV infrastructure in developing countries, fundamentally limits its ability to represent the true state of grid-power access, leading the model to use proximity to HV lines in conjunction with population density, proximity to roads, and the intensity of night time lights (NTL) as proxies for electricity access in a region. Similarly, by only knowing the locations of HV infrastructure, possible grid-extension potential of LV and MV remains unknown.

Fortunately, new machine learning and statistical modeling techniques are poised to shed light on the locations of MV grid networks, providing researchers with previously unavailable geospatial data on the connective and last-mile networks that deliver grid power in developing countries. These new data hold undeniable potential to change tools like OnSSET, but questions about how to best integrate this data and what additional insight it can bring remain unanswered.

1.4 Research Questions

With new geospatial data for MV infrastructure on the horizon, major questions for OnSSET and similar toolkits arise. For instance: what additional value could MV data bring to a tool such as OnSSET? Does the detection of previously invisible MV infrastructure in a community affect how its electricity access status (i.e. “electrified” or “unelectrified”) should be estimated? Should the same logic be used to estimate a community’s electricity access status in the presence of MV as is currently used for HV power lines? This project unfortunately lacks geospatial data for MV infrastructure or ground-truth data for electricity access status, so answering these questions remains out of reach.

Beyond determining the electricity access status of an area, the presence of MV power lines introduces a new class of infrastructure that can be tapped and extended to electrify additional settlements. One major research question for this work follows:

- Should the same model assumptions regarding line capacity (measured in kilowatts) and extension costs (measured in $ per kilometer) be used for MV grid-extension as is currently used for HV?

If MV extension is less expensive than HV, the model will always prefer to extend MV lines over HV, but capacity limits are lower for MV lines than HV. This leads to the second and third major research questions:

- How should the model prioritize grid extensions while remaining within capacity limits?
- How does the addition of MV extension logic impact the OnSSET’s usefulness to electrification planners?

Exploring the question of how to optimize grid-extension with the addition of MV infrastructure represents the bulk of this Master’s Project. It stands to reason that extending from a MV power line should be cheaper than from a HV line (more on grid-extension in Section 2.3), but meaningfully capturing this difference in the OnSSET model represents a major adjustment. MV and HV grid-extensions share similarities - in both cases, investments in upstream grid reinforcements and downstream distribution grids are needed. The potential to extend a MV grid introduces a major challenge that OnSSET does not currently address: HV power lines tapped for grid-extension are treated as having unlimited capacity. While unrealistic for actual HV lines that certainly do have capacity limits, this assumption is *especially* untrue for lower-capacity MV lines. Since capacity constraints are missing from the current grid-extension optimization process, extension of a MV-grid requires an additional step to monitor capacity limits while optimizing extension options.

1.5 Literature Review

This work builds on the current OnSSET model in two key ways: it updates technological parameters to better reflect reality and it introduces grid-extension optimization with capacity constraints for MV infrastructure. Since core model parameters were designed to be changed to fit a study area (e.g. technology costs vary around the world) (OnSSET documentation n.d.), additional literature was not examined to justify this component of my work.

However, my proposed method for modeling MV grid-extension represents a fundamental departure from the method used for HV grid-extension and warrants a deeper look. Surprisingly, no other literature reviewed for this project directly considers line capacity constraints for grid-extension, despite line capacities being considered in other steps, such as last-mile distribution network cost calculations (Python implementation of the OnSSET 2019a). This exemption of capacity constraints for grid-extension is unlikely the result of collective oversight. Perhaps HV grid-extension grid reinforcement costs (more on this in Section 2.3) are assumed to account for capacity upgrades, or extension-line capacity could simply be considered a responsibility for grid planners further down the planning pipeline. Among other reasons, it is also possible that accounting for line capacity limits was thought to introduce too much complexity to the model, proving difficult to implement and slowing down runtime.

MIT's Reference Electrification Model (REM), a techno-economic tool with some similarities to OnSSET, has a more sophisticated approach for calculating grid-extension costs while considering line capacity limits (Ellman 2015). REM identifies "clusters" of individual structures on a map, estimates distribution costs to buildings within each cluster, and calculates grid extension costs to each cluster to compare with mini grid and off-grid technologies (Lee 2018). After identifying neighboring clusters and finding the shortest transmission path connecting them to the grid, REM estimates peak capacity needs for these connections to find the least expensive power lines to meet the peak capacity needs (Ellman 2015). REM's method is very different from OnSSET's extension process (more in Section 2.3), but its inclusion of line capacities provides insight that this is a consideration in other models.

1.6 Motivations for Work

This work was inspired by my concurrent research efforts with a Bass Connections in Energy project at Duke University (Duke Bass Connections n.d.). I serve as project manager for research developing deep learning models to identify transmission and distribution infrastructure in high-resolution aerial imagery, with the ultimate goal of providing data to aid in electricity access planning. Complementing our team's research efforts, I have been exploring how the outputs of our models - geospatial data of infrastructure - could be employed for electricity access planning in developing countries. OnSSET and REM are two prominent electrification planning toolkits that evaluate both on- and off-grid technologies. Since REM has yet to be released to the public, I chose to dive into the OnSSET model to investigate my research questions.

Another motivation for this work stems from what I believe is a systematic over-valuation of off-grid electricity technologies for currently unelectrified populations. In OnSSET, the off-grid technologies (save Diesel and Hydro) have no form of accompanying energy storage or dispatchability, a challenge that greatly inconveniences any load that does not meet intermittent supply. Grid power does not inherently suffer from this problem, and I believe incorporating additional data on MV infrastructure and understanding how it should be valued in the OnSSET model will shed light on how grid and off-grid technologies should be balanced in OnSSET and similar toolkits.

1.7 Paper Objectives and Organization

The objectives of this project can be broken down into two main components: a) to assess core model components that should be adjusted to facilitate the integration of MV grid data, and b) to develop a prototype of a MV grid-extension algorithm using real data and operating under capacity constraints. In addition to the literature review in Section 1.5, a topical literature-review is embedded throughout the Targeted Review of OnSSET Components in Section 2.3.

Section 2 explores the OnSSET model: its uses, inputs and outputs, and most salient components that relate to this papers objectives. Sections 3 of this report outlines proposed changes to the core model and a new add-on tool developed to take the output of an OnSSET analysis and incorporate MV grid infrastructure for optimized MV grid-extension.

Section 4 explores OnSSET in action using data for the country of Afghanistan. Since data on actual MV infrastructure is not currently available for Afghanistan, synthetic data is generated to explore grid-extension scenarios. Section 5 bookends the report with a discussion of the quantitative exercise, conclusions, and implications of this work.

2. The Open Source Spatial Electrification Tool

The OnSSET model was first released in 2015 and has since experienced uptake in use for research and practice, primarily by United Nations organizations and Development Banks (About OnSSET n.d.). Its source code, limited documentation, and example data can be found on the KTH-dESA GitHub (Python implementation of the OnSSET 2019b), provided under an Open Source Initiative MIT License. A more extensive repository for documentation can be found on OnSSET’s ReadTheDocs site (OnSSET documentation n.d.), and its Google Group is a small but collaborative user community (onsset - Google Groups n.d.).

2.1 Overview

OnSSET is a high-level analysis tool for assessing grid and off-grid electricity options for a region to achieve residential electricity access targets by 2030. The region is broken into uniformly-sized grid cells (commonly ranging from 1x1 km to 10x10 km based on the input data resolution), each with unique characteristics that influence electrification costs. The electrification technologies examined include **Grid-Extension** (distribution grid linked to the main grid), **Mini-Grid** (distribution grid using PV, Wind, Diesel, or Hydro), and **Standalone** systems (home PV or Diesel system). For each cell, costs for the different technologies are calculated and converted into a Levelized Cost of

Electricity (LCOE) over the lifetime of the technology. The least-cost option for each cell is aggregated into the following region-wide model outputs:

- Population served per Technology
- New Connections per Technology
- Capacity per Technology
- Investment Costs per Technology

Features

OnSSET was designed to be quick to configure, run, and analyze, using readily available geographic information system (GIS) and country-level data as inputs. Since the model runs quickly even on a computer with modest resources, it excels at running multiple scenarios in succession with varying input parameters. One common scenario analysis examines the relationship between the uptake in technologies such as renewable Mini-Grids versus cheaper standalone Diesel systems under a range of discount rates. In this scenario, increasing discount rates tend to decrease investments in capital-intensive renewables, favoring the lower-capital but higher operating cost Diesel generators. Model outputs are stored in a common spreadsheet file format, which can be imported into popular GIS software for visualization or further processing. The model generates a uniform LCOE for all technologies, facilitating a detailed comparison of trade-offs between technologies.

Challenges

OnSSET trades deeper power system insights for accessibility. The model's resolution is dependent on the resolution of input raster data. It does not perform a power-flow study, consider capacity constraints on HV infrastructure, or meaningfully evaluate the grid generation mix. Other power system models such as OSeMOSYS (OSeMOSYS n.d.) must be linked with OnSSET to provide this additional power system insight, which is a common though difficult process (OnSSET Meeting Notes 2018). Similarly, OnSSET quantifies the costs of reaching specific electrification targets by 2030, but provides little insight into an implementation strategy or timeline. Finally, by comparing grid with off-grid technologies, OnSSET implies that grid reliability will be at least as good as off-grid. In many parts of the developing world, bulk power systems have been shown to be very unreliable, to the point of negating the benefits of grid-connection (Samad and Zhang 2017). On the contrary, OnSSET can also over-estimate the dispatchability of off-grid technologies, leading to muddled comparisons. These are just a few noteworthy challenges with the OnSSET analysis. Others will be discussed in Section 2.3.

Target Audiences/Benefactors

By the standards of a high-level analysis tool, OnSSET is reported to provide a significant speed boost over conventional methods of assessing pathways for grid and off-grid electrification in a study region (Mentis 2017). A team of World Bank researchers carrying out a study on the country of Zambia reported OnSSET reduced the time they needed from 18-24 to 6 months (Mentis 2017). The development banking community, specifically the World Bank, is listed as a one of OnSSET's partners and is among the first groups to make use of OnSSET for studying electrification pathways. Similarly, other global organizations such as the UN Development Programme and UN Department of Economic and Social Affairs are working to increase OnSSET's exposure to planners in developing countries. OnSSET was featured at the Energy Modelling Platform for Africa (EMP-A 2019 n.d.), an event co-sponsored by many of the same international NGOs and development banks. KTH lists private sector partners using their model (Projects n.d.), but it is difficult to determine how widely OnSSET is used outside of the international NGO circuit.

2.2 Model Inputs

The following infographic from KTH outlines the types of data used to calculate Grid, Mini-Grid, and Standalone technologies costs for each cell in the study area.

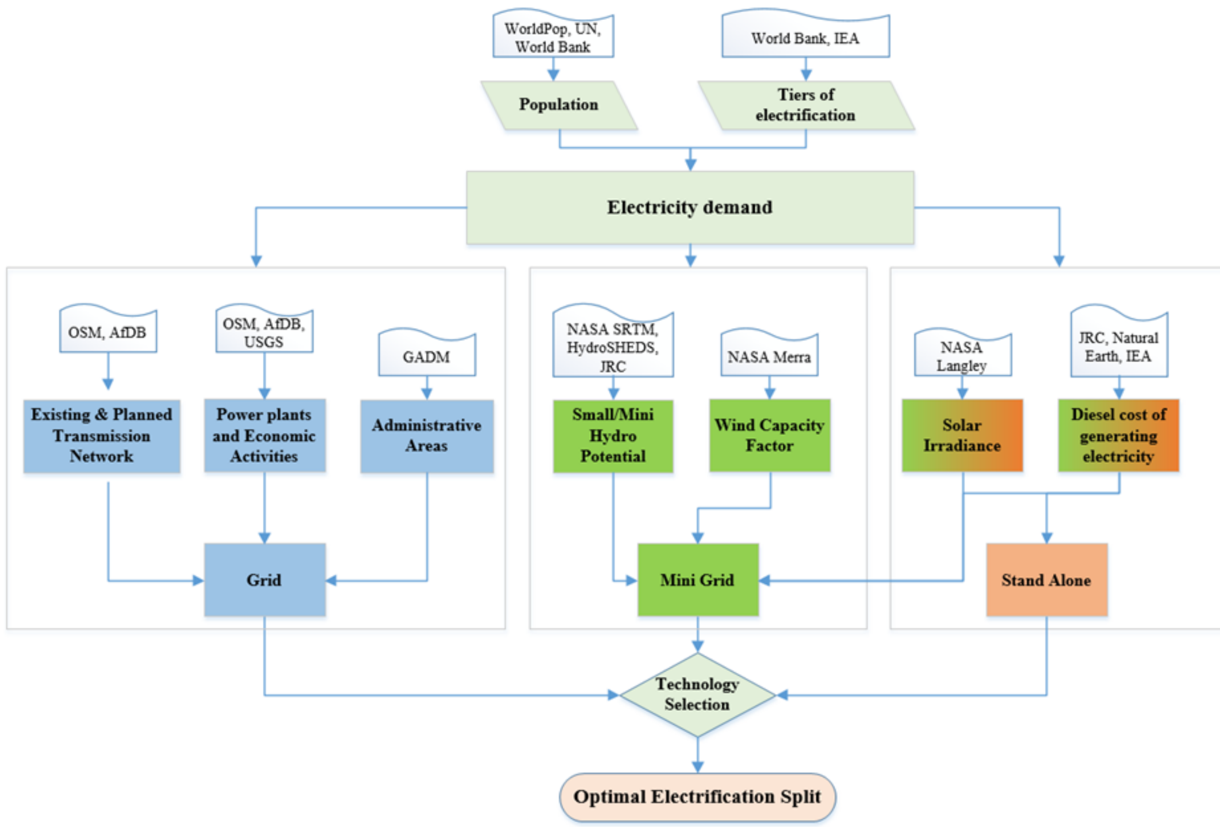

Fig. 1: Model inputs include Population, Access, Geospatial, Technical, and Economic Data (The OnSSET Model — OnSSET documentation n.d.)

The most significant model inputs as they related to this project will be examined in section 2.3.

2.3 Targeted Review of OnSSET Components

This section outlines the OnSSET components that are most relevant to my research questions and work.

Electrification Status

An early step in the OnSSET analysis is determining which cells are already electrified and which are not. Cells cannot be partially electrified, which notably fails to reflect reality for some electrified communities where access is not universal. “Grid densification” refers to an effort to expand access to poorer households within electrified communities (EnDev 2016). Another model assumption is that cells electrified at the beginning of the analysis (i.e. 2015) will remain electrified through the end (i.e. 2030).

A cell’s electrification status is calculated by evaluating its lights visible at night in satellite images, distance to the nearest road and HV grid, and population. If a cell has bright night time lights (NTL), it only needs to have a high population (e.g. >10,000 people) or be close to the grid or a road. If a cell has low NTL, it can only be considered electrified if it has very high population (>15,000), and is close to the grid or a road. The parameters that determine the cutoffs for NTL, road and grid distances are iteratively adjusted until the final population that is considered “electrified” approximates the 2015 national statistic. This calibration step is needed to couple national statistics with the model’s geospatial data, though I have not found any papers rigorously supporting their methods using ground-truth electrification status data.

Discussion:

Determining Electrification Status is a crucial step in OnSSET that utilizes national statistics along with a few indicators to estimate status for each cell in the map. Cutoffs and heuristics are a necessary though error-prone part of modeling. Unfortunately, I could not find any references for the methods chosen for this part of the OnSSET analysis.

Using night time lights (NTL) as a proxy for electricity access is a widespread, though somewhat controversial practice. Satellite images taken at regular times at night (the timing depends on the satellite) are compared to isolate transient light sources. Stable NTLs are compiled into images where each pixel covers approximately $1km^2$ and pixel brightness is calibrated between 0-63, with 63 being the brightest. NTL images span many decades and are widely used in research. A team at the World Bank found NTL to coincide with ground truth data of access in rural villages in India, despite intermittent grid reliability increasing the difficulty calculating stable lights (Gaba n.d.). Despite these positive signs of its usefulness, concerns persist that NTL can under-represent electricity access in rural areas with access but low consumption. This is called “bottom censoring” and occurs when light levels are low enough (due to low population density or consumption) resulting in light to be treated as transient. A similar concern with using NTL as an indicator of access is that residential electricity use may not noticeably permeate the outdoors, particularly in areas that lack street lighting (Khavari and Sahlberg 2017).

Electricity Demand

Electricity demand plays an integral role in calculating the cost of procuring and delivering electricity to previously unelectrified populations. Demand for each unelectrified grid cell is found by multiplying the target Electricity Access Tier by the cell's projected Population in 2030.

OnSSET uses World Bank Residential Energy Access Tiers (ESMAP 2015) to set residential electrification targets for Urban and Rural residents in the study region. Access tiers are numbered 1-5, and for this project range from 7.7 to 598.6 kilowatt-hours per year per capita. They are described by the following table:

Tier	Demand (kWh/person/year)	Electricity Services
0	NA	No access
1	7.7	Task lighting + phone charging or radio
2	43.8	General lighting + fan + television
3	160.6	Tier 2, + Medium power appliances (e.g. refrigeration)
4	423.4	Tier 3, + Medium or continuous appliances (e.g. water heating, water pumping, microwave)
5	598.6	Tier 4, + High power and continuous appliances (e.g. A.C.)

Fig. 2: Electricity Access Tiers Relate Demand to Domestic Electrical Services (ESMAP 2015)

Two Access Tiers, one for Urban and one for Rural populations, are provided as country-wide model parameters. Generally, Urban cells are assigned higher Tier targets than Rural cells.

Cells are designated Urban or Rural based on their 2015 (base year) population and country-level statistics. The model iterates through each cell to calculate an "Urban Cutoff", or population per square kilometer that results in the whole region's Urban and Rural populations to approximate national statistics. If a cell's base-year population exceeds a certain threshold (10,000 by default), it is designated Urban. This "hard" Urban population cutoff creates a discontinuity in demand between cells approaching 10,000 population that is discussed further in Section 4.3. Urban and Rural designation also impacts the assumed population growth rate, which sets the target-year Population, and number of people per household, impacting the costs of electrification technologies. Urban and Rural designations do not change between the base-year and target-year, despite population growth potentially pushing past the "hard" cutoff.

Discussion:

Although I do not modify the demand calculation process with my work, I chose to describe it in detail as both Urban/Rural designation and Tier level choices strongly impact the economic feasibility of grid-extension. Khaveri, a graduate of and researcher at KTH, expands on OnSSET's demand process with more granular designations stemming from survey and geospatial data beyond population density (Khavari and Sahlberg 2017). This approach adds demand classes beyond "Urban" and "Rural" and would likely break up the bimodal demand levels that result from the current process, but requires significantly more data and calculations.

Generally, low demand decreases the competitiveness of Mini-Grid and Grid investments, as higher LCOE's are required to recover fixed costs of distribution infrastructure. This requires increased Stand-Alone technology solutions to reach 100% access in areas with low demand (Moksnes et al. 2017).

It is worth noting that OnSSET's sole focus on residential electrification, despite only 15-20% of electricity being consumed for residential purposes worldwide (Wolfram, Shelef, and Gertler 2012), excludes demand for non-residential productive purposes that would increase demand levels and impact the electrification mix (Korkovelos et al. 2017). It is unclear if the worldwide trend of domestic versus non-domestic consumption holds true for developing countries. Based on its inclusion in OnSSET meeting notes (OnSSET Meeting Notes 2018), incorporating non-residential demand is an area of active investigation for future versions of the model.

Off-Grid LCOE

Finding the levelized cost of power for each Off-Grid Technology is relatively straightforward, using technology-specific parameters and geospatial data for solar, wind, and hydro power potential. Travel time to the nearest large city is a raster layer used to estimate the cost of diesel delivery. The components of Off-Grid Technology LCOE that are most relevant to my research questions involve how off-grid capacity investments are calculated and the lack of storage or hybrid systems.

Installed generating capacity (kW) needs to meet the expected peak load of all newly electrified citizens in a cell. Peak load is a function of the cell's average load (a sum of the access targets for each person in the cell divided by 8760 hours) divided by the specified **base to peak load ratio** (BPLR). BPLR is a percentage that represents how a population consumes electricity: a population with a BPLR of 1 has a constant load through all hours and requires half of the peak capacity as a cell with a BPLR of 0.5. The original OnSSET model assigns different BPLRs to each technology, disproportionately benefiting specific off-grid technologies and implying wildly different user behavior depending on the electrification technology chosen. Grid and Diesel technologies have a BPLR of around 0.5, whereas Wind, PV, and Hydro have BPLR of 0.75, 0.9, and 1 respectively. For Grid and Mini-Grid systems where distribution networks are built, higher peak loads require more costly distribution investments. Capacity factors are also a component of installed capacity costs. PV capacity factor is calculated to be around 0.22 depending on solar resources, and installed capacity costs for PV systems are based on the peak load divided by the capacity factor.

Discussion:

Technologies with higher BPLR require less generating capacity to meet peak demand, which I argue creates an undue burden for people to match their consumption to generation. In the absence of storage or hybrid-technology options (e.g. hybrid solar + diesel), off-grid systems should be made more expensive. Incorporating hybrid-technologies into OnSSET is discussed in OnSSET's most recent meeting notes (OnSSET Meeting Notes 2018), and investigated in recent research (Khavari and Sahlberg 2017), though a clear strategy to competitively value the reliability and flexibility gains of hybrid systems has yet to be established.

Grid Penalty

One of OnSSET's features that makes it stand out from other electrification planning tools is its use of topography-related cost drivers in determining the least cost grid-extensions (Drouin 2018). The Grid Penalty multiplier accounts for the added cost of extending the grid to a cell based on five categories with suitability scores from 1 (least) to 5 (most). The following list contains these five categories and their weights: proximity to the nearest road (5%) and substation (9%), category of land cover (39%), elevation (15%), and slope (32%). The Grid Penalty is capped at 1.25 for the least suitable cells, increasing the costs of MV power lines stretching from the HV line to the cell by 25%. The penalty is applied during the Grid-Extension Optimization step (discussed more below).

Discussion:

The Grid Penalty increases the cost of extending the grid to inhospitable cells, but it does not consider the topography of intermediary cells or impact distribution network costs. If the grid extends across multiple cells to reach a destination cell, only the penalty of the destination cell is used to calculate the extension cost. This intuitively raises the question: if the intermediary cells have higher or lower penalties, won't this skew the true cost of extension? Similarly, the grid penalty is only applied to grid extension costs (i.e. the distance the line travels to the border of the cell in question), though it stands to reason that the same factors increasing the cost of grid-extension should increase last-mile distribution grid investment costs as well. Since both Grid and Mini-Grid require distribution networks that would ostensibly be impacted by the new Grid Penalty costs, Standalone solutions without distribution networks would become more competitive from this change.

Grid Calculations

Calculating the costs of Grid power for cells is OnSSET's most complicated component, taking place in three distinct steps. The first step is the simplest: all cells that were determined to have electricity access at the beginning of the study are assumed to be grid-tied and are provided with the grid's marginal electricity cost ($0.062/kWh in the case of Afghanistan). In the second step, Grid LCOE's are calculated for unelectrified cells that are within 10 km of the existing or planned grid. Finally, all cells that remain unelectrified and fall within 50 km of either the current grid, future grid, or a grid-extension are evaluated for grid-extension. The grid-extension process is iterative and seeks optimal extension paths to minimize extension costs for all feasible cells. Cells that fall outside of this 50 km radius are considered unsuitable for grid electrification and must use off-grid solutions.

Grid LCOE Calculation and Extension Optimization

Similar to Off-Grid LCOE, Grid LCOE represents the price per kWh that is needed to cover generation, O&M, and capital costs for the duration of the study period (2015-2030). It is calculated using the costs of last-mile distribution hardware, home connection costs, O&M costs, average grid electricity rates, cost of capital, upstream reinforcement costs, and grid-extension costs. This section explores components of the LCOE, how they can be adjusted to be more realistic, and how such adjustments can make room for MV-extension.

One major fixed cost for Grid and Mini-Grid solutions is the distribution network. OnSSET uses a formula to estimate the costs of distribution hardware within a cell based on the population, physical area, demand, and peak load. Notably, the unit cost used for the MV distribution line is the same used for HV grid-extension. I contend that this line cost of $9,000/km may be reasonable for distribution but is too low for HV grid-extension, since it fails to account for capacity costs and the full cost of tapping the HV line.

According to the *Guides for Electric Cooperative Development and Rural Electrification*, three-phase 24.9 kV power lines can support a wide range of loads, depending on the conductor used (USAID 2016). The resulting costs per km and capacities may be seen in the following table.

Cost ($ US per Kilometer)	Capacity Limit (Range in KiloWatts)
$8,961	400
$9,140	600-1,600
10,766	1,800-2,500
$15,072	3,000-6,000
$24,314	6,500-7,000

I assume that these costs and line specifications, originally cited for Tomoyo, Bolivia, also apply to Afghanistan.

If a single Urban grid cell contains 15,000 people, each person consumes 160 kWh/year, distribution losses are 18%, and the base to peak load ratio (BPLR) is 0.53, the extension line must meet a peak capacity of **610 kW.** Peak demand is calculated using the following formula:

$$\frac{(Population \times (1 + DistributionLosses) \times AnnualConsumptionPerPerson)}{HoursPerYear} \times BPLR$$

And since the HV grid-extension process can result in many new cells being connected to a single MV line, I propose that the MV line used to extend the HV Grid should support loads of at least 6 MW. Of the MV lines cited above, the least expensive that could support this load costs $15,072/km.

Though OnSSET does not explicitly account for the cost of building a substation at the original point of interconnection with the HV power line, it does implement a catch-all upstream cost calculation. Transmission substation costs range well over $1 million (Pletka et al. n.d.), and it is likely difficult that an optimization algorithm could equitably spread this cost across the cells sharing the interconnection. OnSSET addresses general “upstream network reinforcement” costs from grid-extension with a function that increases costs quadratically for longer extensions. Reinforcement costs may include the addition of new transformers, capacitor banks, upgrading limiting bus or breakers, upgrading lengths of cables, or establishing new substations to account for added network congestion (Cotterman 2017).

OnSSET optimizes HV Grid-Extension by iterating through grid-electrified cells, searching for unelectrified cells within 50 km of any HV infrastructure that can be economically electrified through Grid-Extension. The grid penalty increases cost (i.e. distance) based on the cell’s extension suitability. Each time a new cell is identified for Grid-Extension, the grid effectively “reaches” that cell, making further expansion cheaper for other nearby cells. This process concludes when there are no more cells within 50 km of the original HV line that can afford extension.

The MV extension algorithm I designed (discussed more in Section 3) uses similar inputs and logic to OnSSET’s algorithm, while also adhering to MV-line capacity limits.

3. Integrating MV Lines into the Analysis

Section 3 builds on the analysis from Section 2, implementing targeted changes to the generic OnSSET model (heretofore called the “core” model) to incorporate MV data into the analysis. First, I briefly reiterate the core model components that remain unchanged in my analysis of Afghanistan (Section 4). Next, I outline my changes to the core model that facilitate the addition of MV power lines. Finally, I describe my MV grid optimization algorithm.

3.1 Unaltered Components

Calculating the **Electrification Status** of each cell in the study region (whether it started off considered electrified or not) is a key OnSSET component that remains difficult to meaningfully adjust. Once real MV infrastructure is available for integration with OnSSET, it will be important to consider how distance from the MV grid might be a stronger or weaker indication of electricity access as compared to current assumptions using the HV grid. These new assumptions should be tested with ground-truth data on electrification rates. Since I lack both real MV data and ground-truth electrification status data, I did not modify this component.

Electricity Demand is estimated based on Access Tiers that differ for Urban and Rural populations. In reality, a wider range of tiers should be applied to communities based on their unique residential and productive energy needs. However, implementing a change like this falls outside the scope of this project. As will be seen in Section 4, the current 2-tier system has large impacts on the feasibility of MV extension in the case of Afghanistan.

Although I do not propose any changes to how **Grid Penalty** - the added cost of extending the grid to cells based on their topography - is used to calculate distribution grid costs, in Section 4 I will explore statistics on its apparent impact on the feasibility of MV extension in Afghanistan.

3.2 Core Model Updates

In this section I outline my changes to the core OnSSET model. These changes were selected both to better reflect reality as well as to facilitate the introduction of MV power lines for grid extension. The changes I settled on could be reasonably increased or decreased, so they should be considered parameters. The impacts of these changes will be explored quantitatively in the case study of Afghanistan (Section 4).

By decreasing the **Base to Peak Load Ratio** for Solar PV from 0.9 to 0.75, I increase the installed capacity required for PV systems, effectively increasing the cost of this technology. This change brings consumption patterns of PV closer to parity with Grid. The increase in technology cost for PV could also be thought of as a proxy for the added cost of storage or hybrid generation systems. Since PV (used in both Standalone and Mini-Grid solutions) is the dominant Off-Grid technology, this change increases costs for the majority of cells, making Grid and non-PV Off-Grid technologies more competitive.

I also differentiate the MV lines used for distribution networks from those used for grid-extension and **increase the cost of the MV lines used for HV grid-extension** from $9,000 to $15,072/km. The core model uses the same line cost for both applications, but enforces a low (50 kW) line capacity for distribution line and no capacity for the grid extension. In practice, multiple linked grid extensions could require capacities between 3 and 6 megawatts, so I increased the cost to be commensurate.

This cost increase only applies to HV grid-extensions, and my new MV grid-extension algorithm uses a lower line cost of $9,140/km to account for the lower cost of tapping a MV power line compared with tapping a HV line. Similarly, this cost accounts for a MV line that can handle a lower capacity of 1,600 kW. Since extension costs increase nonlinearly as a function of line cost and distance to account for "grid reinforcement" costs, the price differential between lines used for HV and MV grid-extension increases with longer extensions. This differential accounts for the lower tapping costs for MV versus HV extension. Please, refer to the following plot for a comparison between the two extension costs per unit distance:

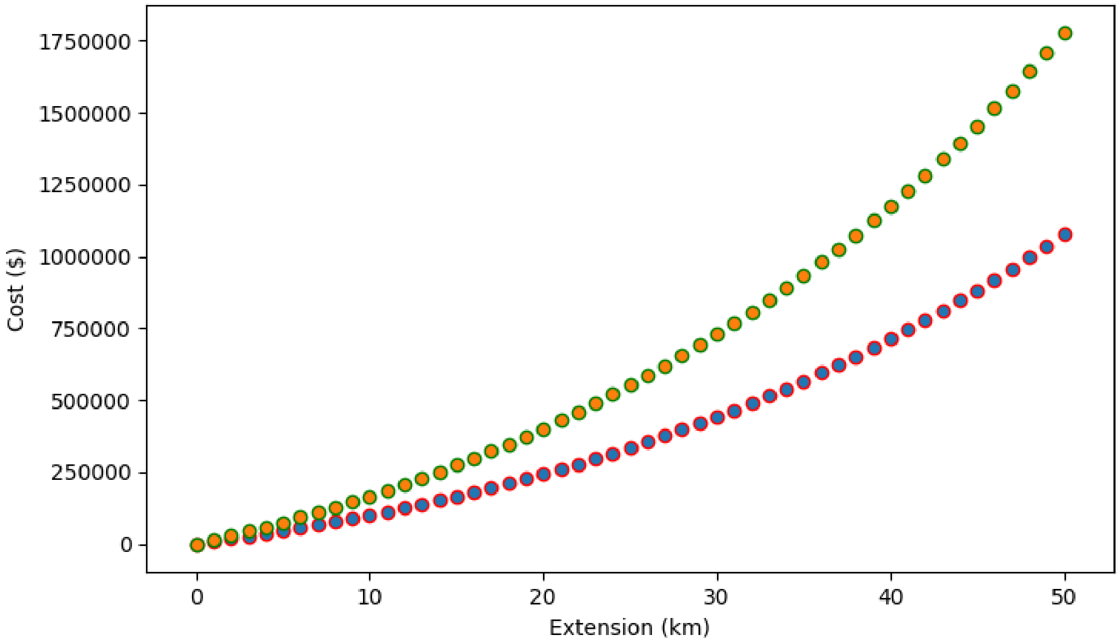

Fig. 3: Extension costs per unit distance of extension. HV-extension (Green-Yellow) costs significantly more that MV-extension (Red-Blue) over longer distances.

MV Grid-Extension is expected to become more competitive as a result of these changes to off-grid PV and HV grid-extension costs. Cells that were unable to afford HV Grid-Extension but *would* benefit from a MV-Extension are referred to as "**feasible**" cells, and represent the focus of my analysis moving forward. In Section 4, I examine the sensitivity of feasible cells to different inputs and use these cells to evaluate my MV grid-extension optimization algorithm.

3.3 MV-Extension Optimization

In addition to changing specific parameters of the core OnSSET model as described in Section 3.2, I wrote an independent Python script to take the output of the OnSSET model and explore feasible cells, to recreate functions of the OnSSET code, and to explore to what extent extending the grid from MV infrastructure could be preferable for these cells to the current HV grid extension with my own MV-extension optimization algorithm. Rather than edit OnSSET's Python code directly, I created separate code to run faster and be easier to debug.

My optimization algorithm routes a MV grid-extension through a grid of cells. I use this algorithm in section 4.4 to model MV grid-extension using a square grid of randomly chosen real feasible cells from Afghanistan. By running many grid-extensions in my algorithm with varying optimization parameters, I explore the implications of how different approaches could benefit or challenge grid planners.

The goal of the grid extension optimizer is to find a path through sequential grid-extensions to cells that maximize annual *Savings* while remaining within the MV capacity limit. Savings is calculated with the following formula:

$$Savings = (OffGridLCOE - GridLCOE) \times Consumption \times (1 + DistributionLosses)$$

Total Savings are not compared directly, rather *Total Savings per Population* provides a metric that identifies the "most profitable" cells without always choosing the largest cell (that may only be moderately profitable). This algorithm mimics the OnSSET grid extension algorithm since it incorporates both grid penalty and network reinforcement costs based the distance to the nearest electrified cell. It differs from the OnSSET extension algorithm since it makes *strategic* choices of which cells to extend the grid to since it must remain within the MV capacity line (1,600 kW for the $9,140 / km MV line).

The algorithm does not conduct an exhaustive search of all possible routes through the feasible cells, as checking every possible permutation of cells is impractical. It considers all unelectrified cells within a 10 km radius of electrified cells, and the cell with the highest savings is chosen to be electrified and all other cells are updated to reflect their distance to the closest electrified cell. This search continues until no feasible cells remain or the total peak load from all newly electrified cells approaches (but does not surpass) the line capacity limit.

I perform scenario analyses on my algorithm Section 4.4 to explore impacts of different algorithm configurations. Running each experiment many times, I explore the average impacts on key metrics (Savings, Number of Cells Electrified, and Electrified Cell Populations) along with plots of expansion paths and implications for grid planners. My primary question revolves around the impact of increasing the algorithm's search distance. This change has large implications for how an extension would appear, be planned and executed by planners, and how it could be perceived by the broader public.

4. Afghanistan Case Study

This section explores the impacts of the changes to the core OnSSET model using real data for the country of Afghanistan. I chose to study Afghanistan primarily because it had a well-curated dataset on which to test model modifications. Such a high-quality dataset was a useful discovery for this project since it was compiled by government analysts and academics and contains some highly technical information and difficult to calculate off-grid technological resources. This dataset was procured from OnSSET's public GitHub repository and developed from collaborative work by KTH on Afghanistan (Korkovelos et al. 2017). Since I was essentially in search of a generic OnSSET data to test the focus of my research (the introduction of MV infrastructure), I chose to use the most official data I could find.

4.1 Unmodified OnSSET Analysis

Here I provide a list of the parameters, both country-wide and approximated using GIS data, that were used in the Afghanistan model.

The resolution of the Afghanistan data is 71km^2 grid cells, equating to 8.4x8.4km resolution grid cells. The 2015 population is 32,527,000 with 26% living in urban areas and the rest rural. The model estimated 44% of the population was Urban, due to the iterative and non-exhaustive modeling process. People per household is estimated at 7 for urban dwellings and 8.1 for rural. The energy access Tiers I selected for urban and rural were 3 and 2, equating to 43.8 kWh/person/year for rural populations and 160.6 kWh/person/year for Urban residents (this consumption level would allow for a fan and TV for rural residents, and the addition of a refrigerator for Urban residents). I selected “High” diesel prices for my scenarios, which equates to $1 / L.

The true electrification rate for 2015 was 30%, though OnSSET’s non-exhaustive calibration process found it to be 36%. Out of 9,274 total grid cells in the country, 236 (2.5%) were calculated to be electrified and 547 (6%) were urban in 2015. These findings suggest that a very small number of electrified cells represent a sizeable proportion of the country’s population. Similarly, the fact that 44% of the population was estimated to be Urban while only 2.5% of cells were classified as urban indicates that Afghanistan is a country characterized by a few large population centers and vast rural areas. OnSSET can accommodate cell areas as low as 1x1km, resulting in much longer run-times as well as higher resolution results. Unfortunately, my dataset was limited to 8.4x8.4km cells, so I could not experiment with the impact of cell size on results.

4.2 Comparing Changes to the Core Model

This section compares select region-wide model outputs of the original OnSSET model, the model with updated Grid cost, the model with updated PV cost, and a model with combined Grid and PV updates. The results of these changes are provided in the following table:

	Original	Grid	PV	Grid + PV
New Connections Grid	16,813,513	16,724,600	19,430,569	18,728,521
New Connections SA_Diesel	7,820	7,820	948,733	1,018,599
New Connections SA_PV	19,847,223	19,936,135	16,292,614	16,924,796
New Connections MG_Wind	-	-	19,671	19,671
New Connections MG_Diesel	-	-	-	-
New Connections MG_PV	422,056	422,056	261,962	261,962
New Connections MG_Hydro	347,237	347,237	484,301	484,301
Total Investment	$7,851,777,209	$7,870,591,574	$8,340,005,307	$8,335,552,478
“Feasible” Cells	1,019	1,027	1,475	1,536

Fig. 4: Comparison of the impacts on population, cost, and feasible cells of the four scenarios. These scenarios include the base case (Original), HV Grid-Extension cost increase (Grid), PV cost increase (PV), and combined case (Grid + PV).

Both changes, the increase in cost of Grid Extension (Grid) and Off-Grid Solar (PV), resulted in increased numbers of feasible cells (bottom row), though increasing the capacity requirements of PV had a far larger impact on feasible cells and other metrics. Notably, the increase in PV prices shifted a combined 3.5 million people from Standalone PV (SA_PV) systems to the Grid and other technologies. The combination of both measures decreased the exodus from SA_PV to about 3 million. The steady increase in feasible cells suggests that both changes impacted feasibility, the focus of this analysis. Judging by the total change in costs, my updated model costs approximately $500 MM more than the Original model to execute.

Figure 5 (below) shows these same results but in a chart. The relative change between SA_PV and Grid is most pronounced between the “Original” and “PV” scenarios.

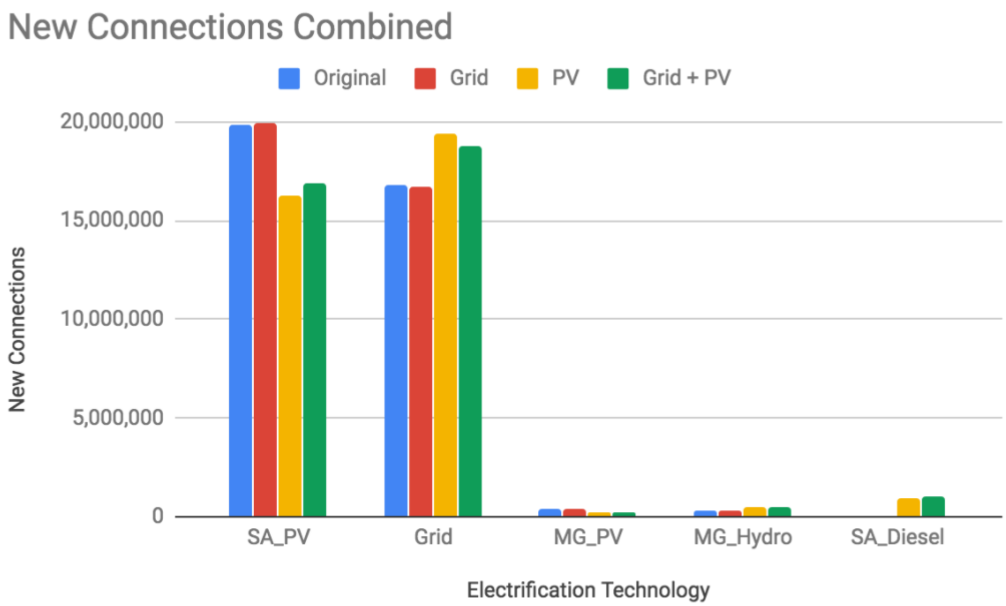

Fig 5: Visual depiction of the population impacts of the four scenarios

Figure 6 shows the final map of least-cost technological recommendations for Afghanistan. This map accentuates the rural nature of Afghanistan. Grid technologies center around urban areas in the country.

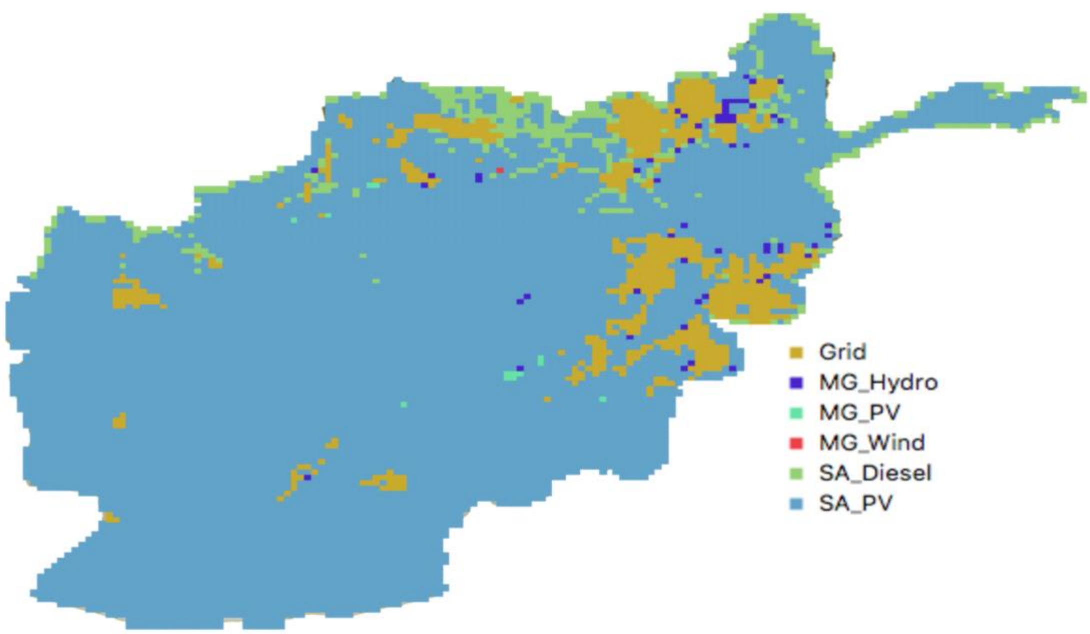

Fig 6: Least-Cost Technologies in Afghanistan

Key Findings

The findings in this section illustrates both the relationship between different model components in general and the impacts of model changes on the Afghanistan dataset in particular. This section should also provide the reader with some grounding in the reasonableness of the methods so far, and serve as a launching point for the examination of MV grid-extension feasibility in Afghanistan.

4.3 MV Feasibility in Afghanistan

This section investigates the principal features that define “feasible” cells, i.e. what drives their ability to afford grid extension? Under what conditions do they remain feasible? Results from the combined model (Grid + PV in the table above) are used moving forward.

First, I explored any geographic relationship between feasible cells and the state of Afghanistan (below). Feasible cells (green) tend to exist in groups, primarily in the North-Eastern part of Afghanistan, and occur in bunches near the current and planned grid (red). This suggests a geographic element to their location (whether this be related to higher population, lower grid penalties, or something else).

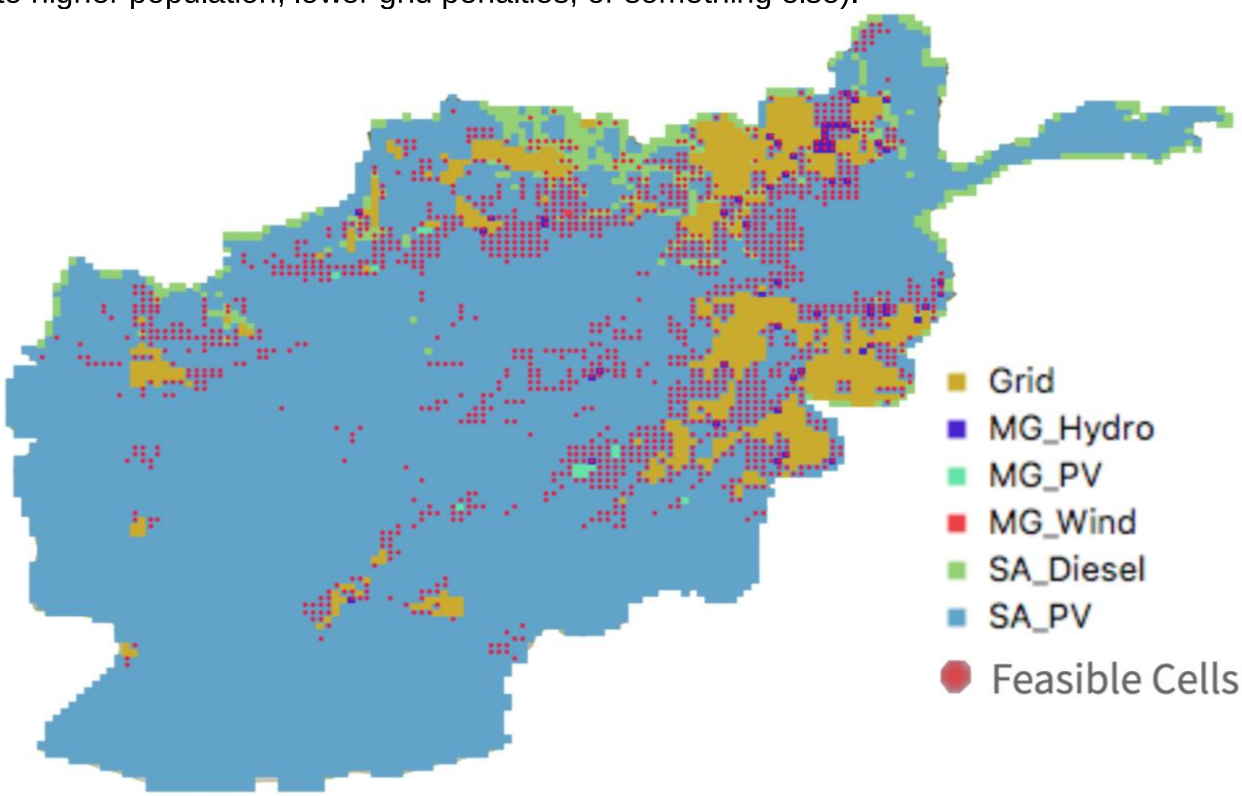

Fig 7: Feasible Cells (Pink) Cluster around Current/Planned Grid Power (Orange)

Feasible cells pictured above are all rural, making up 1,536 out of 9,274 cells in the study region and 18.8% of the 2030 population (= 9,204,725/48,862,843). The cheapest Off-Grid technology alternatives for feasible cells are Standalone Diesel (SA_Diesel) for

116 cells, MG_Hydro for 57, and Standalone PV (SA_PV) for 1,363 cells (making up 89% of feasible cells). The following histogram describes the count of feasible cells in buckets of 500. The distribution skews left, signifying that the bulk of the cells are in the lower end of the population range.

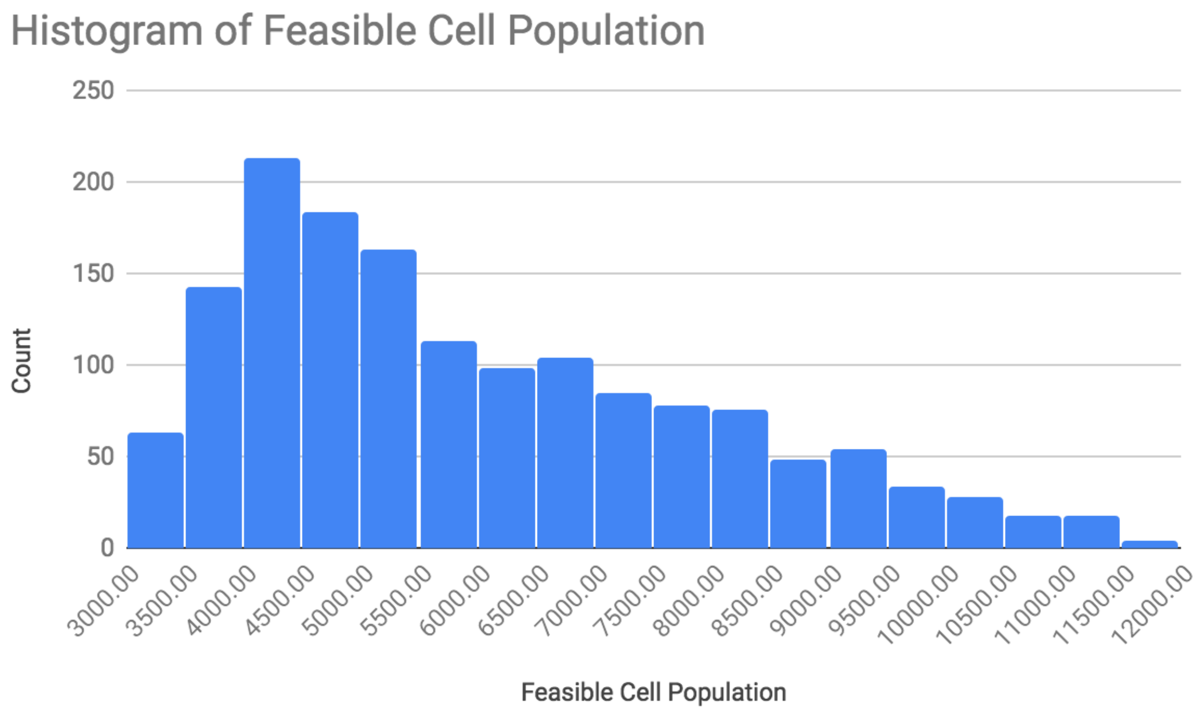

Fig 8: Histogram of Feasible Cell Populations

The next plot assesses the maximum LCOE feasible cells could afford to pay while remaining feasible. There is clearly a relationship between population size and the LCOE cutoff that dictates “feasibility”. Since these values can also be considered the cost of the next cheapest alternative technology, the variability within similarly sized cells captures some of the underlying factors that vary the cost of the other technologies. Notably, the offshoot seen below LCOE of $0.45 represents cells with hydro mini-grids, which provide cheaper power than PV systems.

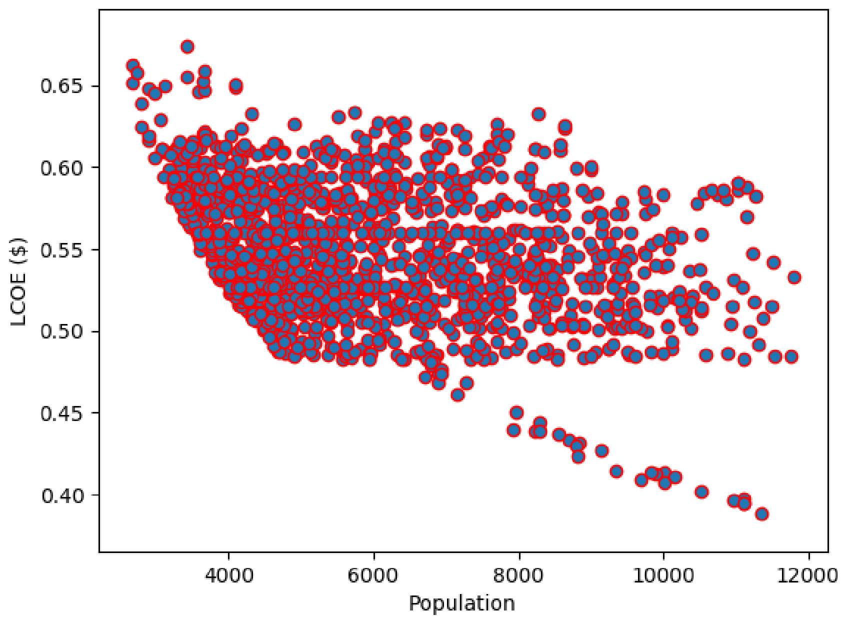

Fig 9: Maximum LCOE Feasible Cells Could Pay for MV-Extension

This next plot illustrates a cleaner relationship between population and the cost of MV grid extension under ideal circumstances (i.e. the cost of connecting the community to a MV grid without needing to pay for any length of extension).

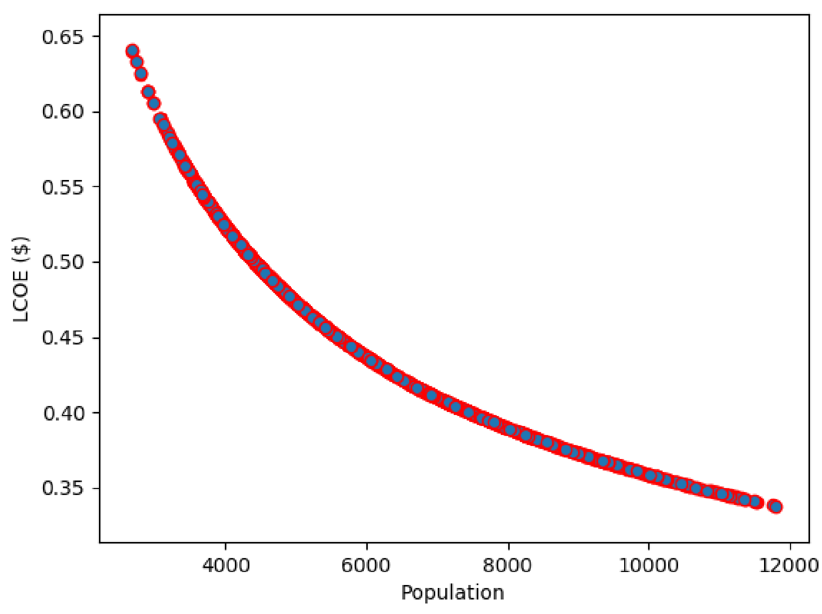

Fig 10: MV Distribution Costs Decrease Non-Linearly for Larger Populations

Notice the non-linear decrease in LCOE as population grows, illustrating the economies of scale that come with higher population grids.

The next plot explores another important question: if these cells are not ideally located, how far could they pay to extend the MV grid while remaining feasible?

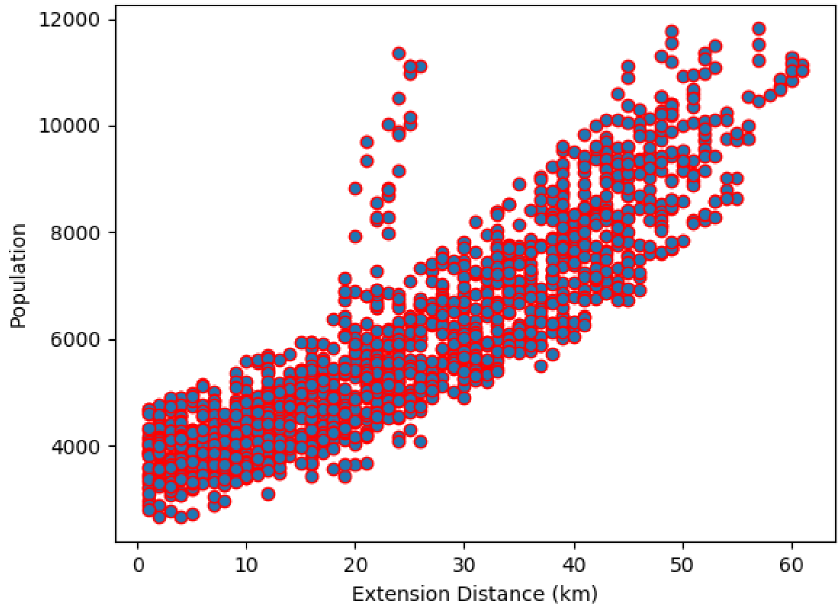

Fig 11: Larger Populations Can Generally Afford Longer Grid Extensions

The variability in this plot is a result of varying grid-penalties (accounting for topographic and other features) and off-grid technology costs. The maximum extension distance increases with cell population, capturing the relationship between gains from grid extension and increasing population. Maximum extension distance is a proxy for the additional costs these cells could bear to extend the grid. As grid extensions increase in length, there is a non-linear increase in the average population needed to support this new length. This relationship reflects the non-linear increase in upstream reinforcement costs incurred for longer extensions (from section 2.3). The small offshoot of high-population cells with low extendability around distance “30 km” are powered by hydro mini-grids, which have a lower LCOE than off-grid solar.

Since all cells are rural and have the same demand per person, the peak load we can expect from each cell is perfectly proportional to the population size. This is reflected in the following figure:

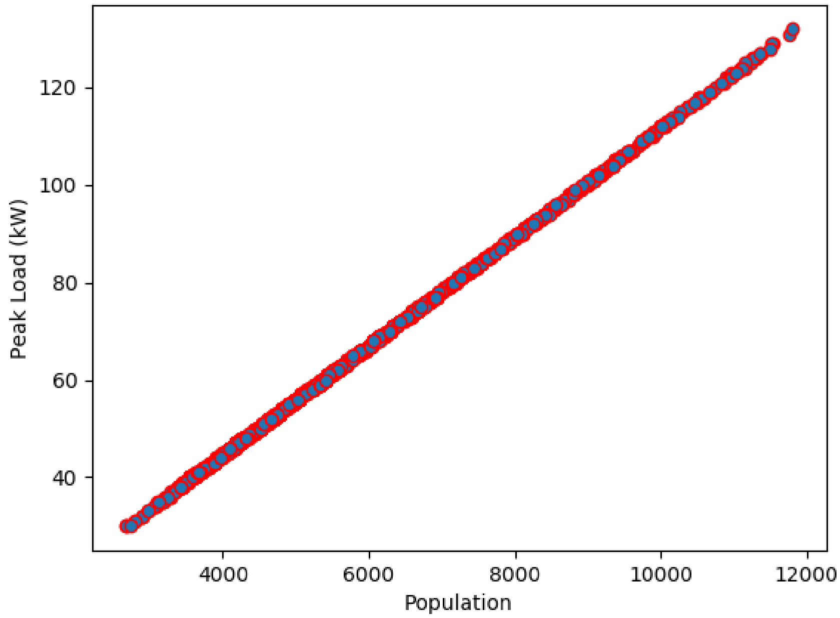

Fig 12: Peak Load is Perfectly Proportional to Population

Key Findings

This section finds that population size, grid penalty, and the costs of alternative off-grid technologies are the driving factors defining feasible cells.

Feasible cells fall within a population range of about 3,000 to 12,000, with more cells in the lower end of this distribution than the upper. The smallest cells represent the minimum population that can afford to pay the high investment costs for a last-mile distribution system. Very few cells in this population band can afford to extend the grid more than a few kilometers (as seen in Fig. 11). The upper end of the feasible population range embodies the discontinuity mentioned in Section 2.3 that results from the somewhat arbitrary “hard” population cutoff dictating which cells are classified as urban or rural. The maximum population (around 12,000, representing the 2030 cell population) fell just below the 10,000 population cutoff in 2015 and were classified as rural, failing to necessitate a higher energy tier which would enable them to afford HV grid extension.

Grid penalties and the costs of competing off-grid technologies both influence how far feasible cells can afford to extend the MV grid. Grid penalties act as a multiplier on extension costs to account for geographies that are more or less ideal for extension, and can only increase the cost of grid extension (and decrease extension distances). Competing technology costs are influenced by natural resource availability (e.g. solar or hydro resources) as well as other factors such as nearest road distance (impacting the cost of diesel). When competing technologies are expensive, feasible cells can afford longer grid extensions than when competing technologies are relatively inexpensive.

Changes made to the core model significantly increased the costs of solar technologies. With solar being the primary secondary technology for feasible cells, more expensive solar both increased the number of feasible cells (as found in section 4.2) and increased the distance feasible cells could afford to extend the MV grid.

4.4 MV-Extension Scenario Analysis

This section evaluates my MV optimization algorithm under two scenarios to explore implications for planners. The scenarios explored include the distance the algorithm is able to look for the next optimal cell to electrify (called the “step size”) and the size of the total matrix in which the algorithm can search for candidate cells. If grid planners choose to optimize their grid extension using longer step sizes, they will likely achieve less orderly grid extensions, since cells with the highest savings per person do not necessarily occur in close proximity to one another. An orderly grid extension would likely result from shorter “steps” as only adjacent cells would be electrified (significantly limiting the algorithm’s search space). A larger matrix (101x101 cells vs 11x11) was also tested with both short and long-steps to see if it affected savings or created any other patterns. Each scenario was run 100 or 1000 times, fewer times for the larger matrices as they had longer run-times. Average metrics from runs were collected to draw generalizable results. The metrics that turned out to be most relevant were:

- **Average Savings**: the total annual savings (in USD) for all electrified cells over their cheapest Off-Grid technology
- **Average Number Electrified**: number of cells electrified
- **Average Cell Size**: average number of people per cell

Results

I found that reach distance had the greatest impact on savings and average cell size and resulted in different-looking paths. Below are two sample plots of the grid extension paths found by the algorithm. The first plot uses short steps (only extending to adjacent cells) while the second uses long steps (extending up to 9 cells away). In both cases, the tables were filled with randomly selected feasible cells, the center-most cell began electrified, and the algorithm extended the grid one cell at a time outward until the peak capacity of 1,600 kW was reached. The patterns described earlier (organized expansion for the short step and disorganized for the long step) can be observed. Notice the “firework” like pattern in the algorithm using long-steps.

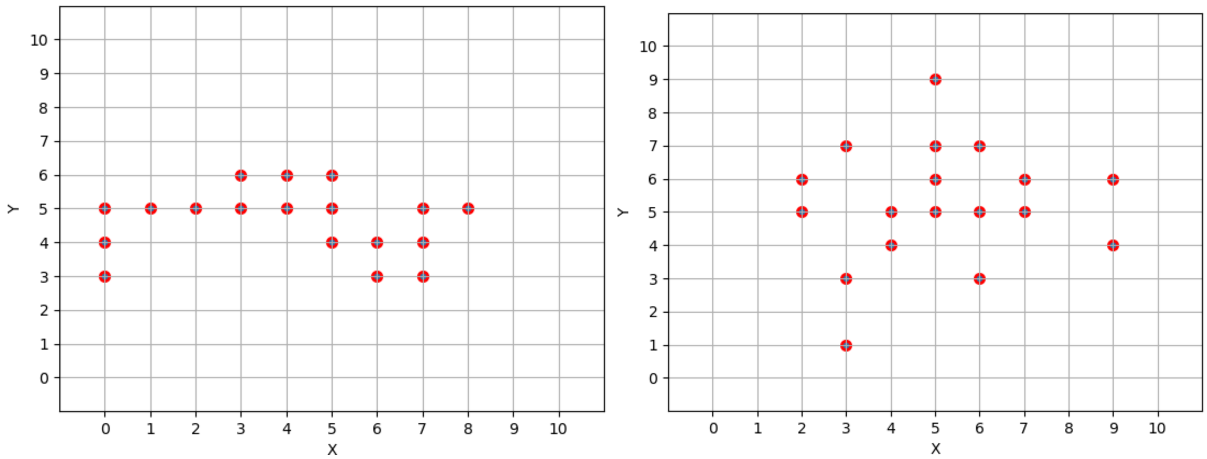

Fig. 13: Shorter Grid-Extension Steps Result in More Orderly Maps (left) as Opposed to Longer Steps (right)

Notably, the long step scenario is able to select the most profitable cells, resulting in average savings of around $7,500 annually as compared with the $6,000 annual savings from the short-step option. The long-step configuration also connected larger cells on average (8,200) versus the short-step (7,200). Larger cells are more profitable to electrify than smaller cells because of the economies of scale mentioned earlier (the same reason why larger cells can afford longer extensions). Electrifying larger cells also resulted in fewer total cells being electrified before the algorithm hits the capacity limit (17 vs 19 cells). This implies that grid planners who selectively electrify the most profitable cells will likely choose larger communities over smaller ones, leapfrogging smaller communities in some cases.

I also ran scenarios using much larger tables (101x101) in an attempt to identify if my tables' small size (11x11) impacted outcomes. I found creating larger spaces for the grid to expand into did not have a noticeable impact on savings or cell sizes. In the following chart, you can see that average cell sizes and savings increase with longer steps, though there is not a noticeable difference from increasing the grid size.

Fig. 14: Longer Steps Increased Annual Savings and Average Size of Electrified Cells.

Discussion

The scenarios discussed in this section by no means represent all of the different configurations of cells or algorithm preferences, but they should provide some insight into likely outcomes for any such algorithm. Real-world grids will be arranged with a mixture of feasible and infeasible cells, requiring longer stretches of extension between infeasible cells. For short-reaching algorithms, too many infeasible cells will behave as a barrier, halting grid extension. In this case, a secondary step should extend the search distance. In the real world grid extension will likely begin at the edge of a connected bloc of cells and work its way outward. These scenarios begin in the middle of a table and have the option to work outward in any direction, likely increasing savings by offering more choices. Similarly, randomly choosing feasible cells to populate the grid assumes no spatial correlation between cells and the features making them feasible. In reality, there will likely be more similarities between adjacent cells than are represented in my examples.

5. Conclusions & Discussion

This section examines the work done in this Master's Project and its implications for OnSSET's users and developers, researchers searching for grid infrastructure data, and electrification planners.

It should first be restated that the results from any OnSSET model depends on underlying model assumptions and design, parameters both user-defined and provided by default, and the study region's input data. It is possible that the cell resolution of the dataset used for these models - 8.4 x 8.4 km cells - played an unknown role in my models. Using higher-resolution data (i.e. cells with a smaller area) would likely differentiate population centers from adjacent low population zones, increasing population density in a subset of cells which could impact the feasibility of technologies that require distribution grids (possibly enabling smaller but denser populations to afford distribution grids). My choice of using a pre-existing dataset restricted my ability to adjust data resolution, so this question remains unanswerable in this work.

The results of the models used in this work necessarily reflect these various inputs, but it is my hope that this work's larger takeaways regarding the interdependence of model components and my justifications for my changes overshadow the actual values I chose to use. In this regard, my changes - decreasing solar's base to peak load ratio from 0.9 to 0.75, selecting the cost of $9,140/km for MV lines with capacity of 1,600 kW, and increasing the cost of HV grid extension lines from $9,000 to $15,072/km - should be considered parameters to be adjusted by future users. Similarly, design choices for the MV grid extension should serve as a proof-of-concept or at least an example-of-concept.

My core model changes increased the cost of solar PV systems and HV grid-extension. I believe these updates better reflect the true costs of these technologies, but there are undoubtedly many other technology parameters that could be justifiably tweaked. I chose these two as they have the biggest impact on the feasibility of MV grid-extension. The net result of these changes was an increase in total feasible cells from 1,019 to 1,536. I found that cells within a population band, about 3,000 to 12,000, that were unable to afford HV grid extension were the best candidates for MV grid-extension. OnSSET determines a cell's electricity demand when it classifies it as urban or rural, with urban cells requiring higher demand than rural. The fact that all 1,536 of the feasible cells were classified as rural suggests that urban classification plays an outsized role determining a cell's ability to afford HV grid-electrification. This divide between outcomes for urban and rural cells is a feature of the two-tier system of demand (discussed in Section 2.3). Hopefully, more levels of demand will be introduced in future versions of OnSSET that will reflect more nuanced variations in demand between populations.

My extension algorithm explored extending a MV grid with capacity constraints to feasible cells. Optimizing cell selection becomes necessary in light of the limited budgets of electrification planners and the presence of capacity limits for MV infrastructure. The optimization target I chose was annual cost savings of investing in MV grid-extension and distribution networks over the current, least cost off-grid technology. My experiments with this algorithm found that larger cells were preferred over smaller cells, and increasing the distance the algorithm could search for candidate cells significantly increased average selected cell population (from 7,200 to 8,200) and savings (from $6,000 to $7,200). Since feasible cells were chosen at random for the algorithm to search through, these results suggest that smaller feasible cells would be uncompetitive in the presence of larger cells (for comparison, the median feasible cell size is about 5,500). Increasing the distance the algorithm could search increases savings by capturing larger cells, but grid planners may not want to pursue this course for a number of reasons. This type of grid-extension clearly excludes smaller cells, raising questions of fairness. Similarly, farther searches results in longer extensions that can shoot out in a disordered fashion, which may pose a challenge for grid planners.

Recommendations

This work has exposed me to the core components of the OnSSET model, which I believe OnSSET **users** should also explore. I would recommend OnSSET users to be aware of the components under the hood and how they impact one-another. Next, I would recommend they consider implementing changes to the model while considering how to best measure the impacts of these changes. OnSSET is imperfect, and users should fully understand its shortcomings and ask “how useful is OnSSET” for achieving their goals. OnSSET provides a high-level tool for comparing electrification pathways and costs, but it is not (and does not purport to be) a grid planning toolkit. These strengths may not be adequate for all users.

For OnSSET’s **developers**, I would recommend re-examining the specific parameters I modified in the core model. Introducing hybrid technologies is already on the roadmap for future OnSSET development, which should alleviate the dispatchability challenge I identified with the solar PV technology. Incorporating MV grid data will prove to be a major model addition, considering all of its implications. If they choose to add a MV grid-extension, I think that capacity constraints and an additional optimization step must be implemented to be realistic. Clearly, my optimization algorithm is more of a proof-of-concept and is not ready to be integrated into OnSSET. First, a method must be introduced to isolate individual MV lines to avoid tapping it more than once (thus, overloading it). This will require a step that traces each MV line back to its HV root. An exhaustive optimization algorithm would then identify the most profitable tap point for each MV line, which could increase the total run time for the OnSSET model. Over-estimating spare capacities on existing MV lines may undo some of the benefits of this addition, and making these estimations should be explored in depth or more conservative estimates should be made. It is unclear if MV-extension should come before or after HV extension, or possibly occur at the same time to maximize savings (or pursue a different optimization target). Further, developers should consider implementing capacity constraints for HV grid-extension as well, since all power lines have capacity limits. This would introduce a slew of additional implementation challenges.

Researchers searching for new classes of electricity infrastructure should consider the needs of models such as OnSSET when designing their own methods. OnSSET uses the distance to nearest infrastructure as inputs for some of its calculations. It does not consider how well-connected that infrastructure is to the broader grid (it would assume islanded infrastructure is grid-tied) or account for noisy geospatial data (i.e. a single falsely-identified transmission tower would be used to “electrify” surrounding cells). As a result, researchers wanting to use their infrastructure data with OnSSET should ensure their grid infrastructure meets a minimum threshold of “connectedness” before assuming that it is viable or capable of being used for grid-extension. Similarly, researchers should focus on high-precision grid maps, to avoid enabling false-positive detection to create erroneous model results. Precision of tower detections should be preferred over recall (the detection of more actual towers). The resulting pipeline for generating data for OnSSET may proceed as follows:

- Precisely identify towers
- If the count of a certain class of towers in an area crosses a threshold consider, that class of tower "identified"
- If "identified" classes of infrastructure can be linked to the greater grid, include it in the OnSSET dataset

Finally, **electrification planners** should consider the nuances of the OnSSET model when engaging with its results. Grid-extension recommendations do not consider political, property, or technical power-balance constraints, so it is incumbent that planners deal with these complexities. If MV grid-extension is introduced into OnSSET, planners will have a new mode of grid-electrification to compare against HV extension and off-grid technologies. If a community is expected to have peak power needs within the capacity limits of a MV power line, then this option may be preferable over HV grid-extension. It is possible that decreasing off-grid technology prices will make those options more viable in the long-run. Planners operate within limited budgets and timelines, and technologies take different lengths of time to deploy. OnSSET does not suggest in what order planners should deploy technologies, so this remains a gap for planners or other software to fill. One byproduct of this project could be the use of the cost-savings metric to identify which cells or technologies are most "profitably" electrified first. This type of analysis could help planners identify "low-hanging fruit" to preferentially electrify. As mentioned previously, caution should be exercised when dispensing scarce resources to some communities and not others.

In summation, I hope that this project makes a compelling case for the addition of MV grid infrastructure into the OnSSET model, outlining its potential uses, and the implications for stakeholders working within the modeling and grid electrification space.

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