ECONOMIC VIABILITY OF MICROGRIDS VS. GRID EXTENSION: A MONTE CARLO ANALYSIS OF RURAL ELECTRIFICATION SOLUTIONS IN THE UNITED STATES

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By:

Anna Helene Amacher

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GRID EXTENSION VS. MICROGRIDS

Anna Helene Amacher

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BESOC

Abstract

This study aims to address the question of cost effectiveness of microgrids versus extending the existing grid in rural regions of the United States through a Monte Carlo Simulation in the statistical tool R. While most literature on the topic is centered on examining the decision-making process in developing nations, this study hopes to address the unique challenges and opportunities within rural electrification in the United States energy transition. This study uses data provided by the National Renewable Laboratory (NREL) and the U.S Energy Information Administration (EIA) to examine the cost-effectiveness of microgrids versus extending the grid in various conditions. After running 7,500 simulation iterations, microgrids demonstrated superior cost-effectiveness with a Net Present Value of \$0.52 million compared to \$0.31 million for extending existing grid infrastructure, and statistical higher probability of being the superior cost-effective option in 72.3% of 7,500 simulation scenarios. Beyond the critical threshold of 12.4 miles from existing grid infrastructure, microgrids are the optimal rural electrification solution, with a median capacity of 92.7 kW.

Keywords: monte carlo simulation, r, net present value, microgrids, electric grid infrastructure, rural, united states, cost effectiveness, utilities.

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1. Introduction

Rural electrification remains a challenge for the United States, where extending and upgrading the electricity infrastructure in rural regions of the United States poses both technical and economic challenges. Electricity infrastructure in the United States is composed of and transported through a complex system referred to as the <u>electrify grid</u> (the grid). The process of delivering electricity requires a complex network of distribution and transmission lines. The United States electricity grid is composed of three larger grids which all public and municipal electricity grids rely on: the Western Interconnection, the Eastern Interconnection, and the Electric Reliability Council of Texas (EIA, 2024). However, while these established regional grids have continued to take on larger energy demand, the grid has seen significant decrease in reliability and as of 2024, 70% of the US grid is over 25 years old (DOE, 2015). While questions of the aging electricity infrastructure are a new field of study within academic research, the topic of rural electrification and the balance of development of the established grid versus the introduction of decentralized energy system, i.e., microgrids, is a newer field of research. For example, a college campus might operate an microgrids with solar panels and battery storage to power the overhead lights in a building, where in rural areas a hospital might use wind turbines and backup generators to maintain operations during a power outage.

While the aging electricity infrastructure the US is an established research topic, the analysis of rural electrification solutions — particularly centralized and decentralized energy systems — remains an underdeveloped area of research in the US context (Uddin et al., 2023). Centralized energy systems operate under the assumption that a power plant is the center of the process and provides services through distribution and transmission lines. While international studies demonstrate that microgrids can significantly improve cost-effectiveness and reliability compared to traditional rural electrification (Soshinskaya et al., 2014; Williams et al., 2015), U.S — specific research on rural microgrid applications is limited. While microgrids can operate in both a centralized and decentralized mode, the defining characteristic of a microgrids is the ability to operate and function in connection with the main grid as well as independently from the grid (Ahlqvist et al., 2022). The ability to operate a part of the grid independently defines decentralized energy systems from traditional centralized systems. In traditional centralized systems, grid operators must predict and match supply to demand a day in advance. Recent studies indicates that the flexibility of utilizing the main grid and operating independently could be most valuable for rural energy access, though more research is needed to provide parameters of these benefits in various regional scenarios and implementation models (Lenhart & Araújo, 2021)

This paper examines the cost effectiveness of microgrids in rural regions of the United States compared to extending the existing grid infrastructure. Given the current challenges in rural electrification in the US, with 70% of U.S infrastructure over 25 years old and rural regions increasingly facing electrification barriers, this research hopes to shed light on the difference between extending the existing grid and adoption of microgrids (DOE, 2022). I aim to contribute to the broader conversation of the energy transition in the US. Furthermore, this research hopes to provide insights into the cost-effectiveness of microgrids in rural areas versus the extending of the traditional grid.

For this hypothesis, this thesis will use a Monte Carlo simulation to examine development and operation cost of microgrids and extending existing grid infrastructure in rural areas. The Monte Carlo simulation model will use data from the from National Renewable Energy Laboratory (NREL) and the US Energy Information Administration (EIA) to model the uncertainties related to electricity pricing, interest rates, cost of initial development, and other relevant metrics to create a data framework to comparatively analyze. By combining the data collected from the EIA and NREL, this data set should give a realistic predictive model that further helps quantify the use-case of microgrids. This model will visually and mathematically demonstrate the conditions where microgrids are the cost-effectiveness option to extending the centralized grid in the rural areas of the US.

This thesis is structured as follows. The next section is a literature review that will provide an in-depth overview of the energy systems in the US from a regulation and economic outlook. The following sections will be a section on theory, which will then lead into an overview of the data and methodology. This thesis will conclude with a summary of the results and findings, which will transition into a discussion section on future research.

2. Literature Review

Although there is a range of research on the general topic of microgrids utilization and adoption, a large part of academic research focuses on microgrids in rural regions of developing countries. In contrast, there are few academic works that address rural energy solutions through the adoption of microgrids in rural regions of the United States. This review hopes to address the gap by exploring the background of energy systems in United

States, the shift in adoption of microgrids through policy and private institutional funding, and the cost of development that is unique to the US.

2.1.1 Background on United States Energy Systems

The United States energy system is an electricity grid, which for the purpose of this thesis will be referred to as the grid, composed of three components: generation, transmission, and distribution. The utility grid is not solely powered with fossil fuels but also incorporates a diverse portfolio of renewable energy — i.e., wind, solar, hydroelectricity. The electric utility grid utilizes high-voltage transmission lines to transport and distribute energy over the entirety of the United States land mass. Transmission lines then deliver power to electric utilities which provides energy services to consumers *(*EIA, 2022).

However, the US utility grid often faces challenges in terms of vulnerable aging infrastructure and increasing public and technical demand for renewable energy solutions (Kaundinya et al., 2009). Accurate data on grid vulnerabilities is scarce due to the topic, which is a national security concern. Therefore, academics and researchers face challenges in obtaining accurate data outside of government research. While rural populations in the US have seen a decrease in recent years (U.S. Census Bureau, 2020), energy demand has continued to increase due to the adoption of electric vehicles and modern farming equipment (Gorjian et al., 2021). This increasing demand in rural regions of the US has prompted a shift towards decentralized energy systems, such as microgrids, which aims to aid in the maintenance and security of the grid, while also engaging the transition from fossil fuel and the integration of renewable energy sources for bulk generation (Soshinskaya et al., 2014).

2.2 Shift to Microgrids

The shift toward microgrids in the United States has been a slow, granular process, with the United States having approximately 460 operational microgrids as of 2024, according to the Navigant Research (2019) there are over 4,400 microgrid projects in the currently across the world (Asmus & Lawrence, 2013; U.S. Department of Energy, 2024). This adoption of microgrids has been influenced by natural disasters and a decline in the reliability of existing grid infrastructure (U.S. Department of Energy, 2022; Infrastructure Investment and Jobs Act, 2021). Unlike the widespread development of microgrids occurring in developing countries, microgrid adoption in the U.S. has occurred in partnership with utilities, rather than as decentralized microgrids that operate independently from the grid (Ajaz & Bernell, 2021).

The contrasting approaches to microgrid adoptions between the US and other countries reflects the different infrastructure challenges. In counties like India and Sub-Saharan Africa, microgrids emerged as alternative solution to extending the existing grid infrastructure, particularly in regions with limited or no access to electricity (Ajaz & Bernell, 2020), (Dadjiogou et al., 2024). In these studies, performed in India and sub-Sahara Africa, Ajaz and Bernell explain that it is often microgrids that provide an immediate and cost-effective soliton to energy accessibility issues due to the infrastructure and economic constraints of the given region. In rural regions in developing countries where the existing grid infrastructure is already underdeveloped, microgrids provide a rapid deployment option that can serve communities without electricity access without the constraints of an infrastructure project.

In contrast, the approach to microgrids in the US reflects a vastly different regulatory and investment landscape, as the US has an established energy landscape and an electric utility industry that operates the dominant grid system. With the US energy market structure being primary aligned on large-scale utilities, microgrids must integrate with the established centralized grid infrastructure (Platt et al., 2011).

The US approach to microgrids is shaped more by broader renewable energy policy framework rather than by specific regulations and incentives for microgrid (Ajaz & Bernell, 2020; Dadjiogou et al., 2024). First, the Investment Tax Credit (ITC) provides incentive that can support microgrid development, but its focus is on solar photovoltaic (PV) solar installations and battery storage capacity, with credits of 0.55 or 0.33 cents per Kilowatt (Internal Revenue Service, 2024), and the Bipartisan Infrastructure Law Smart Grid Grant program (SGG), which funds grid enhancement technologies including microgrids (Bipartisan Infrastructure Law, 2021; *Smart Grid Grants*, 2022) .

These policies and federal funding incentives have encouraged public utilities to focus their investments on supporting clean energy goals overall, rather than just on microgrid development (Lenhart & Araújo, 2021). Public utilities have served as the primary operators of microgrids through two approaches. First, public utilities have established pilot testbed networks to optimize microgrid technologies that can seamlessly integrate into existing grid infrastructure (Lenhart & Araújo, 2021). Second, public utility companies have adopted the use of community microgrids, which are energy systems that can work independently or in conjunction with the main grid (Gui et al., 2016). Community microgrids that are developed in conjunction with utilities bring direct resilience and economic benefits to the community in which it operates (Gui et al., 2016, Lenhart & Araújo, 2021).

Efforts to encourage the adoption of microgrid programs began to formally gain traction in 2008 with the introduction of the Renewable and Distributed Systems Integration program (RDSI) (Feng et al., 2018). Since then, the U.S. has continued to develop incentives for microgrid investment and adoption across various sectors, particularly among utilities and industrial companies (Feng et al., 2018). Academic researchers emphasize that microgrid development in the United States has been a relevant strategy in the modernization of the existing grid infrastructure while also allowing for the integration of renewable energy sources (Ajaz & Bernell, 2020; Dadjiogou et al., 2024).

2.3 Cost Effectiveness of Microgrids

The analysis of microgrid cost effectiveness requires a special approach that is beyond traditional financial framework. For this study, I will utilize data from William et al. (2015) and Gissey et al. (2020) to provide foundational context to quantify the cost effectiveness of microgrids. According to Gissey et al. (2020), if using net present value (NPV) when determining the overall profitability of a microgrid project there must be consideration between the initial cost of set up and the discounted future rate of cash flow.

While traditional NPV calculates the difference between present cash flow and outflow over a set time, Gissey et al. argues that to account for the nature of energy pricing and the high capital investment into any microgrid project, researchers should use a System-Based Net Present Value (SNPV). SNPV extends beyond NPV by measuring the overall profitability of an energy investment (Gissey et al., 2020). According to

NREL's 2018 study, microgrid development costs range from $2-5 million per megawatt (MW), with 75% attributed to installation costs (Giraldez et al., 2018).

The cost-effectiveness of microgrids versus grid extensions depends on two key factors: (1) population density, and (2) the distance from the centralized grid. In rural communities seeking reliable energy access, the combination of population density and distance from the existing grid infrastructure often makes traditional grid extensions economically unfeasible (Williams et al., 2015). Their analysis found that for communities more than 10 miles from an existing grid infrastructure, microgrids were 40-60% more cost-effective than the alternative (Williams et al., 2015).

Investment into microgrid projects faces three types of risks: technical risks (system integration and reliability), financial risks (high capital costs and specialized labor forces), and operation risks (maintenance challenges) (Shahzad et al., 2023). These risk factors, combined with limited long-term data on performance, have led to funding challenges and slower adoption rate in the U.S.

Two contrasting microgrids implementations in the U.S demonstrate different approaches to microgrid adoption in the U.S. The Blue Lake Rancheria Microgrid (BLR) in rural California represents successful rural application, combining solar power and battery storage to save $200,000 annually in energy costs while maintaining critical operations during grid outages (Schatz Energy Research Center, 2024). The BLR microgrid installation proved cost-effectives given the projects distance from the main grid infrastructure, with the $6.3 million project achieving positive returns within five years due to transmission costs and significant improved reliability (Blue Lake Rancheria MG, 2024).

In contrast, the Brooklyn Microgrid demonstrates urban implementation possibilities, using blockchain technology to enable peer-to-peer energy trading among community members. This project reduces transmission losses and provides grid support services valued at $150,000 annually, while allowing participants to trade locally generated solar energy directly with neighbors (Brooklyn Microgrid, 2024). The Brooklyn project's success in an urban setting highlight how microgrids can enhance grid resilience even in areas with existing infrastructure.

Economic analysis of microgrids and extending the centralized grid is the operation cost and initial capital cost. According to a NREL 2018 study, microgrid that operate under a community microgrid, which are microgrids that operate with one or more substations to serve a localized area, had the lowest mean cost of $2.1 Million /MW (Giraldez et al, 2018). However, institutional and utility microgrids have the largest mean cost of $3.3 Million/MW and $2.6 Million/MW (Giraldez et al, 2018). The economic comparison between microgrids and grid extension can be evaluated using Net Present Value (NPV), where NPV indicates the value of an asset, in this case extending the grid versus Microgrids by adding the cashflow of the present value of all future cash flows that said asset will generate:

$$NPV = \frac{R_t}{(1+i)^t} \qquad \text{Equation 1}$$

Where R_t represents cash flow in period t, r is the discount rate, and t is the time (time horizon) (Fernando, 2024).

The economic viability of microgrids compared to extending existing grid infrasture can be mathematically compared using NPV. To comprehensively evaluate the economic variability of microgrids in rural electrification, this thesis will use a Monte Carlo simulation approach.

3. Methodology

This thesis employs a Monte Carlo simulation in R to model the uncertainties in comparing microgrids versus grid extensions. This statistical approach generates random sampling to determine a range of outcomes, enabling a broader understanding of the economic viability and risk profiles of both options (Kurt, 2020). The decision to choose between developing infrastructure for microgrids and extending the traditional grid is critical to the energy resilience of rural United States. By using a Monte Carlo simulation, this study was able to consider uncertainties, generating 7,500 iterations and providing statistical results to give insight into the cost-effectiveness of decentralized microgrids and extending the existing grid infrastructure.

In this methodology section, I aim to provide a framework for comparing cost-effective of decentralized microgrids and extending the existing grid infrastructure. The Monte Carlo simulation analysis used incorporates electricity price, installation costs, distance factors and operation and maintenance costs (O&M). The data utilized to generate a realistic model are from the electricity price annual average for all 50 states for the years 2023-2024, and the industry benchmarks of installation and operating cost for both infrastructure development cases.

3.1 Data Sources

Electricity pricing data was collected from the 2023 U.S Energy Information Administration's 2023 State Electricity Profiles (EIA); the data covers all 50 states.

Furthermore, this dataset illustrates the regional variations of state electricity profiles between the different states, for example Hawaii average retail price was 38.60 cents per kilowatt-hour versus North Dakota 8.03 cents per kilowatt-hour. By utilizing all 50 state profiles from this dataset instead of selecting the ten most rural states, the prices follow a normal distribution rather than treating each state price as equal. Using a normal distribution best reflects clustering of prices around regional variations.

While this analysis uses retail electricity prices, which aligns with similar studies by Hafez & Bhattacharya (2017) and Quashie et al. (2018), some researchers use wholesale prices instead. Retail prices were chosen because they best incapsulate operation, fixed costs, and the regional variations in pricing parameters. The choice to use retail prices is crucial when comparing microgrids and grid extensions, as the fixed costs of maintenance is calculated in retail electrify prices. Furthermore, retail prices are reported consistently and across all states, allowing for a comprehensive data frame to be built.

Table 1

State Electricity Profiles

State	Avg. Retail Price (cents/kWh)	State	Avg. Retail Price (cents/kWh)
Hawaii	38.60	Illinois	11.75
California	24.87	Indiana	11.49
Connecticut	24.24	Alabama	11.47
Massachusetts	23.21	Georgia	11.06
New Hampshire	22.96	Ohio	11.04
Rhode Island	21.62	Montana	10.97
Alaska	21.41	Mississippi	10.95
Maine	20.84	Missouri	10.87
New York	18.28	Kansas	10.80
Vermont	17.53	Tennessee	10.69

New Jersey	15.27	Virginia	10.68
Maryland	14.34	North Carolina	10.61
Michigan	13.68	South Carolina	10.50
Florida	13.53	South Dakota	10.49
Nevada	13.09	Oregon	10.32
Delaware	12.85	West Virginia	10.26
Wisconsin	12.72	Texas	10.04
Pennsylvania	12.57	Kentucky	9.96
Minnesota	12.21	Arkansas	9.73
Arizona	12.19	Washington	9.58
Colorado	11.76	New Mexico	9.47
Illinois	11.75	Iowa	9.42
Indiana	11.49	Oklahoma	9.30
Alabama	11.47	Nebraska	9.14
Georgia	11.06	Idaho	9.08
Ohio	11.04	Utah	9.03
Montana	10.97	Louisiana	8.91
Mississippi	10.95	Wyoming	8.39
Missouri	10.87	North Dakota	8.00

Note. Data adapted from "Average Retail Price of Electricity to Ultimate Customers by End-Use Sector" by U.S. Energy Information Administration, 2023, State Electricity Profiles. Retrieved from https://www.eia.gov/electricity/state/

Infrastructure cost data for microgrids was collected from the 2018 National Renewable Energy Laboratory's (NREL) Phase I Microgrid Cost Study. This study establishes a baseline mean installation cost of $3,500/kW of capacity and a defined $750/kW for standard deviation for site variations, the installation mean. The parameters of microgrid capacity were also derived from this study, with the range of 5kW for a single-home (SH) to 1,500kW for community-scale infrastructure (*Table 2*). To focus on community-scale microgrids, I selected three capacity levels: 5 kW, 25 kW, and 250 kW. The mean capacity was calculated as:

$$\frac{(5 + 25 + 250)}{3} = 93.33\ kW$$

The empirical standard deviation is 113.9 kW however, I choose to use 50 kW to better reflect the operating conditions of rural electricity needs. Furthermore, utilizing a 50 kW standard deviation preventing the generation of unrealistic scenarios where microgrid capacity would exceed typical rural demand electricity profiles.

Table 2

NREL Capacity vs. Service capability

Capacity (kW)	Service
5	Single home
25	Small residential cluster (10 homes)
250	Medium community (100 homes or 3 retail buildings)
500	Large community installation (200 homes or 5-6 retail buildings, or 1 supermarket/clinic/school)

Note. Adapted from "NREL Microgrid Cost Study: Phase 1" by J. Giraldez, F. Flores-Espino, S. MacAlpine, and P. Asmus, 2018, National Renewable Energy Laboratory (NREL/TP-5D00-67821), p. 28. https://doi.org/10.2172/1968345

The data used for grid extension costs was derived from the Department of Energy (DOE) estimates from the guidelines in “Off-Grid or Stand-Alone Renewable Energy Systems.” The DOE estimated range is the baseline for this study about the cost of extending the grid range is $15,000 to $50,000 per mile; this wide range accounts for regional and geographical variations. The distance from grid infrastructure data was collected from the United Nations Development Programme and Deloitte's October 2021 report on rural electrification strategies (Deloitte Touche Tohmatsu, 2021). The interest rate data from U.S. Treasury's Annual Interest Rate Certification for Fiscal Year 2023;

specifically for the purpose of this study the 3.5% rate for the 23–28-year maturity range was chosen because the scope of this study is 25 years. The simulation uses a time horizon of 25 years was used because 25 years is the average lifespan of a microgrid (Mîndra et al., 2024). Figure 1 represents the cost comparison framework used to simulate NPV with the given data used.

Table 3

Economic Parameters and Simulation Results by Infrastructure Type

Category	Parameter	Microgrid	Grid Extension
Initial Cost	Base Installation Cost	$3,500/kW	$15,000-$50,000/mile
	Capacity/Distance	93.33 kW ± 50 kW	0-25 miles
	Cost Distribution	Normal	Uniform
Financial	Interest Rate	3.5% ± 0.5%	3.5% ± 0.5%
	Project Lifetime	25 years	25 years
	O&M Costs[a]	3.0%	2.0%
Operational	Daily Consumption	500 kWh ± 100 kWh	500 kWh ± 100 kWh
	Annual Variation	±10%	±10%
Simulation Results	Mean NPV[b]	$0.52M ± $0.11M	$0.31M ± $0.09M
	Annual O&M Cost	3% of capital cost	2.0% of capital cost

Note. Parameters based on Monte Carlo simulation with 7,500 iterations. O&M = Operations and Maintenance. aPercentage of total capital costs. bNPV values expressed in millions of USD (2024).

3.2 Monte Carlo Simulation

This study implements a Monte Carlo simulation, which was conducted in R (ver. 4.1.0). The simulation uses various libraries the tidyverse, ggplot2, knitr, and MASS. For each 7,500 iterations, the simulation generated random values within specified distributions:

The interest rate data used follows a normal distribution with a mean of 3.5% and standard deviation of 0.5%. The choice to use normal distribution for interest rate to realistically reflect the practical considerations of interest rate modeling because interest rates often use normal distribution due to central economic regulators aiming to maintain stable rates around a specific target. Electricity prices were chosen based on data specific distribution.

Installation costs for microgrids follow a normal distribution due to the estimated value of $1,500/kW, however grid extension costs use a uniform distribution between $15,000-$50,000 per mile. The choice to utilize two different distributions represents the key difference between cost structures for installation of microgrids versus grid extension development. For distance factors, normal distribution reflects a typical rural deployment of microgrids and grid extensions. Since this study is not focused on one specific region or community, using uniform distributions reflects semi-realistic rural location and scenarios in which microgrids may be utilized in rural regions of the US. The distribution range is set at a minimum of 0 miles and maximum of 25 miles based on the brief report by Deloitte submitted to the United Nations Development Programme (2021).

4. Results

The Monte Carlo simulation provides outputs that illustrate initial findings on the economic viability of microgrids versus extending the existing grid in rural regions of the United States. Initially, the iterations performed were 10,000 to account for outliers and marginal error. However, to optimize the output, I chose to use 7,500 for computational efficiency. The quantity of 7,500 iterations was chosen based on an iteration test conducted with three different iteration counts: 5,000, 7,500, and 10,000. The mean of all random numbers generated in each test is shown in *Table 4*.

Table 4

Iteration Test Results

Iteration Number	Mean of all Random Generated
5,000	0.01635341
7,500	0.009467275
10,000	0.01338482

Note. Results from Monte Carlo simulation testing conducted using R (Version 4.1.0). Random number generation performed using rnorm function with the mean = 0.

The lack of variance between the mean of each function are all close to zero (between 0.016 and 0.009) which is consistent with the simulation being stable. Furthermore, the results are converging around zero, however I used a normal distribution embed code called rnorm which generates random numbers from a normal distribution with a mean of 0.

Table 5

Summary of Monte Carlo Simulation Results

Metric	Value
Mean Microgrid NPV	$0.52M
Mean Grid NPV	$0.31M
Mean NPV Difference	$0.21M
Probability Microgrid Better	72.3%
Median Distance	12.4 miles
Median Capacity	92.7 kW

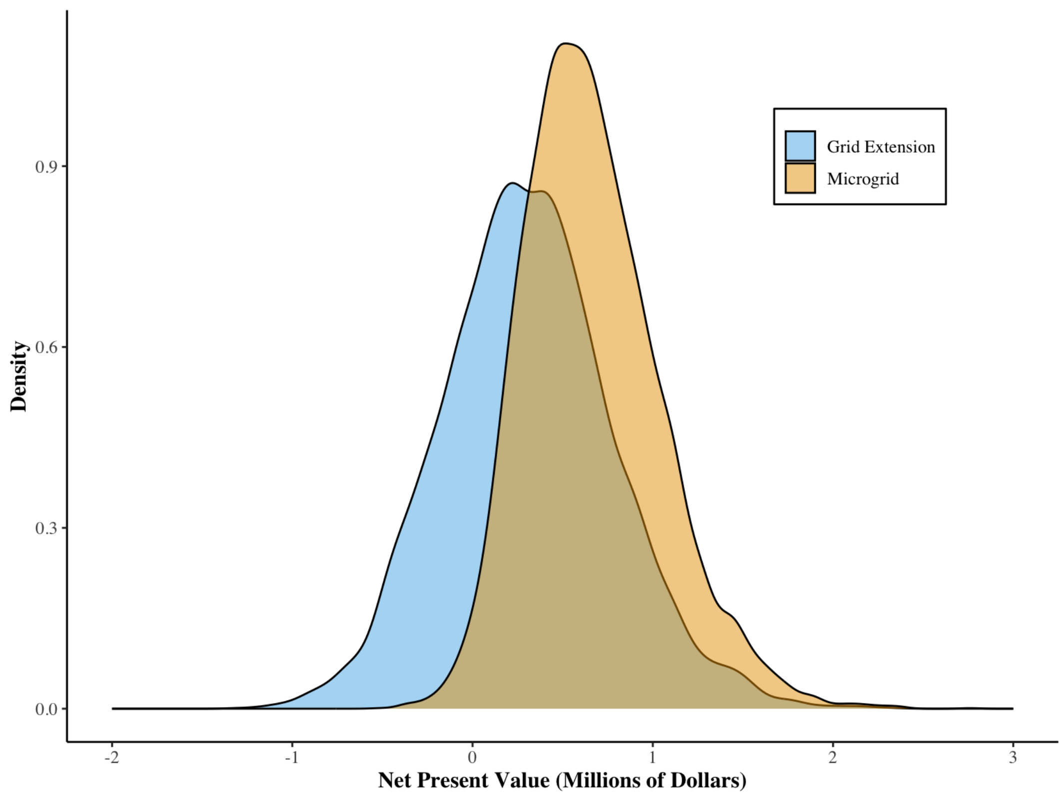
Note. Values represent outcomes from 7,500 iterations of Monte Carlo simulation. NPV values are expressed in millions of USD (2024).

The simulation results provide a simplified statistical result that microgrids have a clear advantage over grid extensions. The mean NPV for grid extensions was $0.31

million, lower than the mean NPV for microgrids projects which was \$0.52 million. The mean difference in NPV is \$0.21 million with microgrids having an economic advantage over grid extensions. Furthermore, the simulation results showed that with the median capacity of 92.7 kW, microgrids were more cost-effective in 72.3% of simulated iterations. Figure 1 clearly visualizes the NPV distribution.

Figure 1

NPV Distribution: Microgrid vs Grid Extension



Note. Values represent outcomes from 7,500 iterations of Monte Carlo simulation. NPV values are expressed in millions of USD (2024).

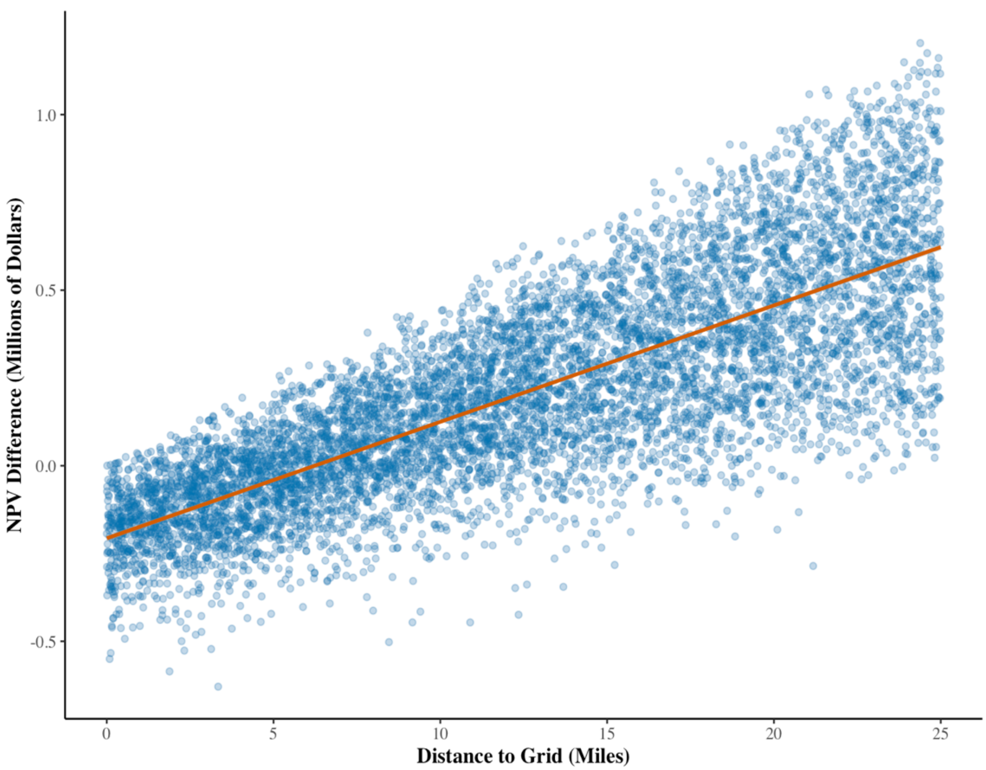
The simulation results also identified a key distance threshold that determines the cost-effectiveness of microgrids compared to grid extensions. This critical threshold is 12.4 miles from the existing grid infrastructure. When a rural community is over 12.4

miles from the grid, the initial cost of microgrids is less than the cost of extending grid infrastructure.

Moreover, the simulation revealed a clear linear relationship between distance from the grid and the economic advantages of microgrids. As the distance between a rural electrification project and the existing grid increases, the net present value (NPV) advantage of microgrids over grid extensions grows proportionately. In other words, the further a rural community is from existing grid infrastructure, the more cost-effective microgrids are as a solution to rural electrification.

Figure 2

NPV Difference vs Distance to Grid



Note. Scatter plot demonstrates relationship between distance from existing grid infrastructure and NPV differential. X-axis represents distance in miles; Y-axis represents

NPV difference in millions of USD (2024). Dotted line indicates critical threshold at 12.4 miles. Based on 7,500 Monte Carlo simulation iterations.

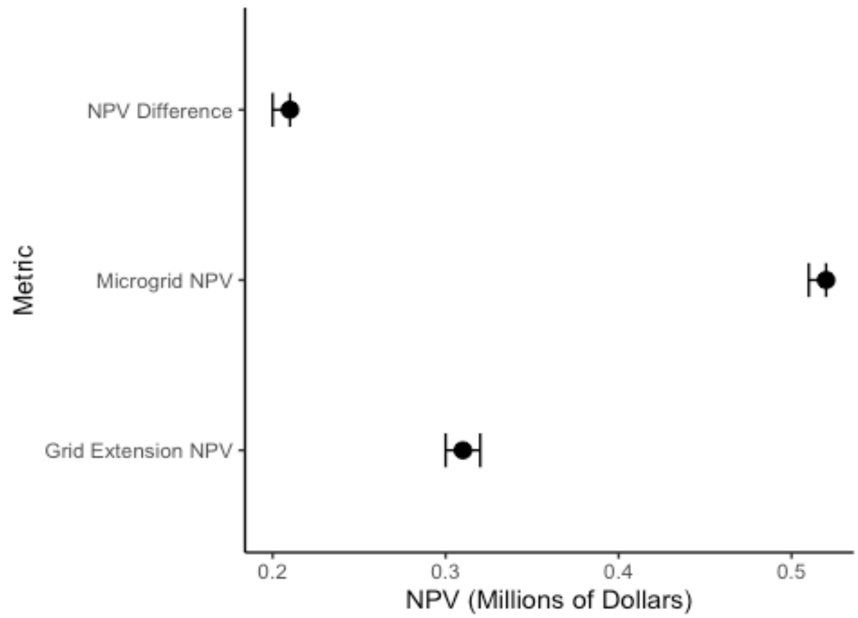
In Figure 2, the visualization of NPV distribution highlights the economic variability and advantage of microgrids over grid extension projects, while NPV Difference vs Distance to Grid plot (Figure 8) illustrates the linear relationship between distance from the grid and NPV of microgrids. These visuals support the findings of the advantage of microgrids versus extending existing grid infrastructure in rural communities of the United States, and in turn provide a clear decision-making framework for rural electrification.

4.1 Confidence Intervals

The Monte Carlo simulation (N=7,500) shows strong statistical evidence that microgrids are more cost effective than extending existing grid infrastructure in rural electrification. The analysis shows that the mean NPV for microgrids is $0.52 million (95% CI: $0.51M-$0.52M) outperform grid extensions at $0.31 million (95% CI: $0.30M-$0.32M). The NPV difference of $0.21 million (95% CI: $0.20M-$0.21M) represents the 68% better return for microgrids. The narrow confidence intervals and small standard error (≤0.01) show the results of the analysis are statistically reliable across all variables. Figure 3 presents the visual representation of these confidence intervals.

Figure 3

95% Confidence Intervals for NPV Analysis



Note: This analysis uses Monte Carlo simulation with 7,500 iterations to model NPV outcomes for rural electrification projects. Confidence intervals are calculated at 95% confidence level.

5. Discussion

First, the superior cost-effectiveness of microgrids is evident in higher mean of NPV ($0.52 million vs. $0.31 million for grid extension) and the probability of 72.3% of scenarios resulting in microgrids as a more cost-effective solution. Second, the economic advantage of microgrids becomes stable once the project is passing the critical threshold of 12.4 miles from existing infrastructure.

The Monte Carlo Simulation used in this study and the approach to understand the research question reveal several important limitations that must be acknowledged. The time/temporal constraint of a fixed 25-year time horizon is an assumption made based on the limited literature available on this relatively new technology. Furthermore, electricity prices and interest rates were utilized from prior public data but do not reflect current data and policy implications. Beyond the financial metric limitations, this study did not consider geographic considerations because of the challenge of incorporating terrain-to-cost modeling and limited data available on distance factors that directly address this thesis. Technical parameters also face limitations due to standard technology costs; the costs of microgrids and grid extensions rely heavily on the demand from regulators, government institutions, and consumers and therefore are elastic. While these limitations are critical to address, they do not undermine the validity of the analysis but rather provide a greater use case scope. Further research might address these limitations through more sophisticated modeling and data sources.

6. Conclusion

The Monte Carlo simulation analysis provided statistical evidence that for the cost-effectiveness of microgrids as rural electrification solution compared to extending the existing grid infrastructure. The analysis, based on 7,500 iterations, proved evidence that microgrids achieve a mean Net Present Value (NPV) of $0.52 million compared to $0.31 million for grid extensions, the mean NPV difference is $0.21 million in favor of microgrids implementations. The analysis also indicated that microgrids were more cost-effective solution to rural electrification in 72.3% of scenarios, with a median capacity of 92.7kW.

A critical finding of this thesis was the identification of the 12.4-mile threshold distance from the existing grid infrastructure. The 12.4-mile threshold can serve as a decision-making parameter for utilities and community officials when elevation electrification solutions in rural regions of the US. Beyond this distance, the economic case for microgrids adoption strengths compared to extending existing grid extension solutions.

In this study, there are several limitations for considerations and suggest directions for future research. The simulation relied on a fixed time horizon of microgrids and standard cost assumptions that are not specific to regional variations (i.e., terrain, cost of building, utility, and community budgets). Future research should address these limitations:

- Incorporate geographic and terrain specific cost variables.
- Long term operational data analysis.
- Assessment of regional pricing differences.
- Integration of real-time market data and policy impacts.

However, despite these limitations, the finding of this study contributes to evidence supporting microgrid adoptions in rural regions of the United States. While regulatory and financial challenges remain as adaptation barriers, the demonstrated cost-effectives of microgrids suggest that microgrids should be utilized a primary solution for rural electrification, especially in rural communities that are beyond the identified threshold of 12.4-miles threshold from existing grid infrastructure.

Appendices

Monte Carlo Analysis Code Documentation

Data Preparation

```
rural_prices <- data.frame(
  State = c(
    "Alabama", "Alaska", "Arizona", "Arkansas", "California",
    "Colorado", "Connecticut", "Delaware", "Florida", "Georgia",
    "Hawaii", "Idaho", "Illinois", "Indiana", "Iowa", "Kansas",
    "Kentucky", "Louisiana", "Maine", "Maryland", "Massachusetts",
    "Michigan", "Minnesota", "Mississippi", "Missouri", "Montana",
    "Nebraska", "Nevada", "New Hampshire", "New Jersey", "New Mexico",
    "New York", "North Carolina", "North Dakota", "Ohio", "Oklahoma",
    "Oregon", "Pennsylvania", "Rhode Island", "South Carolina",
    "South Dakota", "Tennessee", "Texas", "Utah", "Vermont",
    "Virginia", "Washington", "West Virginia", "Wisconsin", "Wyoming"
  ),
  Price = c(
    11.47, 21.41, 12.19, 9.73, 24.87,
    11.76, 24.24, 12.85, 13.53, 11.06,
    38.60, 9.08, 11.75, 11.49, 9.42,
    10.80, 9.96, 8.91, 20.84, 14.34,
    23.21, 13.68, 12.21, 10.95, 10.87,
    10.97, 9.14, 13.09, 22.96, 15.27,
    9.47, 18.28, 10.61, 8.03, 11.04,
    9.30, 10.32, 12.57, 21.62, 10.50,
    10.49, 10.69, 10.04, 9.03, 17.53,
    10.68, 9.58, 10.26, 12.72, 8.39
  )
)


rural_prices <- rural_prices[order(-rural_prices$Price), ]

knitr::kable(rural_prices,
      col.names = c("State", "Price (cents/kWh)"),
      caption = "State-Level Electricity Prices (2023)",
      align = c("l", "r"),
      digits = 2)

national_average <- mean(rural_prices$Price)
sd_rural_prices <- sd(rural_prices$Price)
print(national_average)
```

```
[1] 13.436
```

```
print(sd_rural_prices)
```

```
[1] 5.794902
```

```
microgrid_generation_capacity <- data.frame(
  Capacity = c(5, 25, 250, 500, 1500),
  Possible_Connections = c(
    "1 home",
    "10 homes",
    "100 homes or 3 retail buildings",
    "200 homes or 5-6 retail buildings or 1 supermarket or 1 health clinic or 1 small
school",
    "600 homes or 15-20 retail buildings or 4 supermarkets or 4-5 health clinics or
2-3 schools or 1 hospital"
  )
)
community_capacities <- microgrid_generation_capacity$Capacity[c(1, 2, 3)]
mean_community_capacity <- mean(community_capacities)


calc_se <- function(x) {
  sd(x) / sqrt(length(x))
}
iteration_test <- function() {
   n1 <- 5000
   n2 <- 7500
  n3 <- 10000
result1 <- mean(rnorm(n1))
  result2 <- mean(rnorm(n2))
  result3 <- mean(rnorm(n3))
  print(abs(result1))
  print(abs(result2))
  print(abs(result3))
}
```

Primary Simulation Function

```
run_monte_carlo_simulation <- function(n_simulations = 7500) {
  results <- data.frame(
    interest_rate = numeric(n_simulations),
    electricity_price = numeric(n_simulations),
    microgrid_capacity = numeric(n_simulations),
    distance_to_grid = numeric(n_simulations),
    microgrid_npv = numeric(n_simulations),
    grid_npv = numeric(n_simulations)
  )

  for(i in 1:n_simulations) {
    results$interest_rate[i] <- rnorm(1, mean = 3.5, sd = 0.5) #data from average
of interest rate 2023-2024
```

```
    results$electricity_price[i] <- rnorm(1, mean = national_average, sd = sd_rural
_prices)
    results$microgrid_capacity[i] <- max(0, rnorm(1, mean = 93.33, sd = 50))
    results$distance_to_grid[i] <- runif(1, min = 0, max = 25) # un dis. from UNDP
Task Force, converted to miles from km

    microgrid_installation_cost <- results$microgrid_capacity[i] *
  rnorm(1, mean = 2120, sd = ((3334.788 - 1430.805)/4)) #SD: Calculated from t
he IQR range ($3,334,788 - $1,430,805)/4000 to convert to kW

    grid_extension_cost <- results$distance_to_grid[i] *
      runif(1, min = 15000, max = 50000) # Using uniform distribution for cost rang
e per mile


daily_consumption <- rnorm(1, mean = 500, sd = 100)
annual_consumption <- daily_consumption * 365 * rnorm(1, mean = 1, sd = 0.1)
annual_revenue <- results$electricity_price[i] * annual_consumption

    microgrid_om <- microgrid_installation_cost * 0.03 #(2019 Electricity ATB - 201
9 ATB - Utility-Scale PV - Commercial PV - Battery Storage - Nuclear - Biopower,
2019)
    grid_om <- grid_extension_cost * 0.02 #(World Bank, 2017)


    time_horizon <- 25
    time_series <- 0:time_horizon

   microgrid_cashflows <- c(-microgrid_installation_cost,
                         rep(annual_revenue - microgrid_om, time_horizon))
  results$microgrid_npv[i] <- sum(microgrid_cashflows /
                                  (1 + results$interest_rate[i])^time_series)

  grid_cashflows <- c(-grid_extension_cost,
                    rep(annual_revenue - grid_om, time_horizon))
  results$grid_npv[i] <- sum(grid_cashflows /
                             (1 + results$interest_rate[i])^time_series)
  }


  results$npv_difference <- results$microgrid_npv - results$grid_npv
  return(results)
  if(use_rural) {
      results$electricity_price[i] <- rnorm(1, mean = rural_average, sd = rural_sd)
    } else {
      results$electricity_price[i] <- rnorm(1, mean = national_average, sd = sd_rur
al_prices)
    }
}
```

Results

```
set.seed(123)
simulation_results <- run_monte_carlo_simulation()

npv_data <- gather(simulation_results, key = "Type", value = "NPV", microgrid_n
pv, grid_npv)
npv_data$Type <- factor(npv_data$Type,
                        levels = c("grid_npv", "microgrid_npv"),
                        labels = c("Grid Extension", "Microgrid"))

ggplot(npv_data, aes(x = NPV/1e6, fill = Type)) +
  geom_density(alpha = 0.5) +
  scale_fill_manual(values = c("Grid Extension" = "#56B4E9",
                               "Microgrid" = "#E69F00")) +
  theme_classic() +
  labs(x = "Net Present Value (Millions of Dollars)",
       y = "Density") +
  xlim(-2, 3) +
  theme(
    legend.position = c(0.8, 0.8),
    legend.title = element_blank(),
    text = element_text(family = "serif", size = 12),
    axis.title = element_text(face = "bold"),
    legend.background = element_rect(color = "black", linetype = "solid", linewidth
= 0.5)
  )

set.seed(123)
simulation_results <- run_monte_carlo_simulation()

npv_data <- gather(simulation_results, key = "Type", value = "NPV", microgrid_n
pv, grid_npv)
npv_data$Type <- factor(npv_data$Type,
                        levels = c("grid_npv", "microgrid_npv"),
                        labels = c("Grid Extension", "Microgrid"))

ggplot(simulation_results, aes(x = distance_to_grid, y = npv_difference/1e6)) +
  geom_point(alpha = 0.3, color = "#0072B2") +
  geom_smooth(method = "lm", color = "#D55E00", se = TRUE) +
  theme_classic() +
  labs(x = "Distance to Grid (Miles)",
       y = "NPV Difference (Millions of Dollars)") +
  theme(
    text = element_text(family = "serif", size = 12),
    axis.title = element_text(face = "bold")
  )

summary_stats <- data.frame(
  Metric = c("Mean Microgrid NPV", "Mean Grid NPV", "Mean NPV Difference",
             "Probability Microgrid Better", "Median Distance", "Median Capacity"),
  Value = c(sprintf("$%.2fM", mean(simulation_results$microgrid_npv)/1e6),
```

```
    sprintf("$%.2fM", mean(simulation_results$grid_npv)/1e6),
    sprintf("$%.2fM", mean(simulation_results$npv_difference)/1e6),
    sprintf("%.1f%%", mean(simulation_results$npv_difference > 0) * 100),
    sprintf("%.1f miles", median(simulation_results$distance_to_grid)),
    sprintf("%.1f kW", median(simulation_results$microgrid_capacity)))
)

kable(summary_stats, caption = "Summary of Monte Carlo Simulation Results")
```

Summary of Monte Carlo Simulation Results

```
calculate_confidence_intervals <- function(data, conf_level = 0.95) {
  n <- length(data)
  se <- sd(data) / sqrt(n)
  degrees_of_freedom <- n - 1
  t_value <- qt((1 + conf_level) / 2, degrees_of_freedom)
  margin_error <- t_value * se
  mean_value <- mean(data)

  return(list(
    mean = mean_value,
    lower = mean_value - margin_error,
    upper = mean_value + margin_error,
    se = se
  ))
}
```

Confidence Interval Analysis

```
confidence_results <- data.frame(
  Metric = c("Microgrid NPV", "Grid Extension NPV", "NPV Difference"),
  stringsAsFactors = FALSE
)

microgrid_ci <-
calculate_confidence_intervals(simulation_results$microgrid_npv)
grid_ci <- calculate_confidence_intervals(simulation_results$grid_npv)
diff_ci <- calculate_confidence_intervals(simulation_results$npv_difference)

# Add results to the dataframe
confidence_results$Mean <- c(microgrid_ci$mean, grid_ci$mean, diff_ci$mean) /
1e6
confidence_results$Lower_CI <- c(microgrid_ci$lower, grid_ci$lower,
diff_ci$lower) / 1e6
confidence_results$Upper_CI <- c(microgrid_ci$upper, grid_ci$upper,
diff_ci$upper) / 1e6
confidence_results$SE <- c(microgrid_ci$se, grid_ci$se, diff_ci$se) / 1e6
```

```
# Round all numeric columns to 2 decimal places
confidence_results[, 2:5] <- round(confidence_results[, 2:5], 2)


print("95% Confidence Intervals (in millions of dollars):")
```

```
## [1] "95% Confidence Intervals (in millions of dollars):"

print(confidence_results)

##              Metric Mean Lower_CI Upper_CI   SE
## 1      Microgrid NPV 0.52     0.51     0.52 0.00
## 2 Grid Extension NPV 0.31     0.30     0.32 0.01
## 3     NPV Difference 0.21     0.20     0.21 0.00

# Perform t-test
npv_ttest <- t.test(simulation_results$microgrid_npv,
                    simulation_results$grid_npv,
                    conf.level = 0.95)

# Print t-test results
print("\nStatistical Significance Test:")

## [1] "\nStatistical Significance Test:"

print(paste("p-value:", format.pval(npv_ttest$p.value, digits = 3)))

## [1] "p-value: <2e-16"

print(paste("Statistically significant difference:", npv_ttest$p.value < 0.05))

## [1] "Statistically significant difference: TRUE"


ggplot(confidence_results, aes(x = Metric, y = Mean)) +
  geom_point(size = 3) +
  geom_errorbar(aes(ymin = Lower_CI, ymax = Upper_CI), width = 0.2) +
  theme_classic() +
  labs(title = "",
       y = "NPV (Millions of Dollars)") +
  coord_flip()
```

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