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Guidelines & best practices for mini grid optimization in African context

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Summary

Rural electrification strategies are essential for addressing the energy access gap in remote and underserved areas. These strategies vary in scope and approach, each addressing specific challenges related to infrastructure, affordability, and sustainability. The main rural electrification strategies include grid extension, stand-alone solutions, and mini-grids [4]. Grid extension, although effective in densely populated areas, faces significant challenges in rural regions due to high costs, long distances, and geographical barriers. Off-grid solutions, such as solar home systems, are more cost-effective and scalable for isolated households but often struggle with limited energy capacity and reliability. In contrast, mini-grids?small-scale, decentralized energy systems?emerge as a promising solution for rural electrification [5]. Mini-grids can operate independently or in conjunction with the main grid and provide a reliable source of electricity to communities, addressing both residential and productive uses of energy. These systems are particularly suitable for remote areas with scattered populations and can be powered by renewable energy sources such as solar, wind, or hydro. However, the deployment of mini-grids faces its own set of challenges, including high upfront capital costs, regulatory barriers, and the need for community engagement to ensure long-term sustainability. Despite these hurdles, mini-grids hold significant potential in delivering affordable, reliable, and sustainable energy solutions for rural populations.

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EXECUTIVE ABSTRACT

Deliverable 13.3: Guidelines & Best Practices for mini grid optimization in African context provides comprehensive guidelines and best practices for mini-grid optimization in the African context. It emphasizes the importance of energy access for sustainable development, particularly in rural and remote areas. The document outlines various electrification strategies, including grid extension, stand-alone solutions, and mini-grids, highlighting the advantages and challenges of each approach.

The evolution of mini-grid technology is discussed, with a focus on the transition from diesel-powered systems to hybrid and smart mini-grids that integrate renewable energy sources and advanced energy management systems. The document also covers power generation technologies, energy storage solutions, distribution infrastructure, and smart technologies for remote monitoring.

A significant portion of the document is dedicated to comprehensive energy planning, which involves understanding the local context, assessing renewable resources, and estimating load demand. The importance of designing technical solutions that are tailored to the specific needs of the target communities is emphasized, along with the need for effective business models and complementary activities to ensure long-term sustainability.

Additionally, the document delves into optimization frameworks, which are crucial for effective mini-grid planning and implementation. It discusses various mathematical optimization techniques, including Linear Programming (LP), Mixed-Integer Linear Programming (MILP), and Non-Linear Programming (NLP). These techniques help in identifying the optimal configuration of mini-grid components, ensuring cost-efficiency and reliability. The optimization frameworks section also covers the use of software tools for energy modelling, such as HOMER, MicroGridsPy, and PyPSA. These tools facilitate the analysis of different scenarios, enabling planners to make informed decisions about system design and operation.

The document concludes with a detailed case study on the optimization of a mini-grid system in Faza, Kenya, a minigrid that has been scenario of a SETADiSMA data collection campaign in 2023, showcasing the application of state-of-the-art energy modelling and optimization techniques. The case study highlights the impact of varying energy demand, technology costs, and system architecture on capacity allocation and economic performance.

In conclusion, the document describes a holistic approach to mini-grid optimization, combining technical, economic, and social considerations to achieve sustainable energy access in rural and underserved areas.

1. INTRODUCTION

A. ENERGY AND SUSTAINABLE DEVELOPMENT

Sustainable Development Goal 7 (SDG 7) aims to ensure universal access to affordable, reliable, sustainable, and modern energy for all by 2030, recognizing energy access as a crucial driver of economic development, social equity, and environmental sustainability. Energy access is central to achieving multiple other SDGs, from health [1] and education [2] to gender equality and economic growth [3]. The first target of SDG 7 is dedicated to addressing global electricity access, a challenge that is particularly significant in rural and remote areas, where infrastructure gaps and affordability issues prevent the delivery of reliable power. Overcoming the so called "last mile" challenge requires innovative solutions, tailored policies, and infrastructure investments that prioritize inclusivity and sustainability.

B. ELECTRIFICATION STRATEGIES

Rural electrification strategies are essential for addressing the energy access gap in remote and underserved areas. These strategies vary in scope and approach, each addressing specific challenges related to infrastructure, affordability, and sustainability. The main rural electrification strategies include grid extension, stand-alone solutions, and mini-grids [4]. Grid extension, although effective in densely populated areas, faces significant challenges in rural regions due to high costs, long distances, and geographical barriers. Off-grid solutions, such as solar home systems, are more cost-effective and scalable for isolated households but often struggle with limited energy capacity and reliability. In contrast, mini-grids—small-scale, decentralized energy systems—emerge as a promising solution for rural electrification [5]. Mini-grids can operate independently or in conjunction with the main grid and provide a reliable source of electricity to communities, addressing both residential and productive uses of energy. These systems are particularly suitable for remote areas with scattered populations and can be powered by renewable energy sources such as solar, wind, or hydro. However, the deployment of mini-grids faces its own set of challenges, including high upfront capital costs, regulatory barriers, and the need for community engagement to ensure long-term sustainability. Despite these hurdles, mini-grids hold significant potential in delivering affordable, reliable, and sustainable energy solutions for rural populations.

C. MINIGRIDS TECHNOLOGY

I. EVOLUTION OF MINI-GRID TECHNOLOGY

Mini-grids have evolved through three primary generations, adapting to technological advancements and energy access needs. The first-generation mini-grids were predominantly diesel-powered, with limited efficiency and high operational costs, often exceeding $0.50/kWh. The second generation introduced hybrid systems that combined renewable energy sources such as solar, wind, and biomass with diesel backup, reducing costs to $0.30–$0.40/kWh. The third generation, or smart mini-grids, integrates advanced energy management systems, IoT-based monitoring, and predictive maintenance, further optimizing costs and performance. These advancements have contributed to lowering the Levelized Cost of Electricity (LCOE), particularly in Sub-Saharan Africa, where the average LCOE for solar hybrid mini-grids ranges between $0.20 and $0.30/kWh, depending on location, financing conditions, and system scale [6].

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II. POWER GENERATION TECHNOLOGIES

Mini-grid power generation depends on the availability of local renewable resources and technological maturity. Solar photovoltaic (PV) systems are the most widely deployed, with efficiency levels reaching 18%–22% and a capacity factor of 18%–25% in Sub-Saharan Africa. Wind turbines offer higher capacity factors of 30%–40%, but their viability is site-specific, requiring wind speeds above 5 m/s for economic feasibility. Micro-hydro mini-grids, where applicable, provide the highest efficiency of 70%–90% and a capacity factor of 50%–60%, but their deployment is limited to suitable water resources. Biomass and biogas systems operate at efficiencies of 20%–30% and are often used in agricultural regions with available feedstock. Hybrid mini-grids that integrate multiple generation sources typically achieve overall system efficiencies of 60%–80%, improving reliability and cost-effectiveness compared to single-source generation [5].

III. ENERGY STORAGE SOLUTIONS

Storage is a critical component of mini-grids, especially for solar- and wind-based systems, where energy generation fluctuates. Lithium-ion batteries, now the dominant storage solution, offer round-trip efficiencies of 80%–95% and a lifespan of 10–15 years. Lead-acid batteries, while cheaper, have lower efficiency (60%–80%) and shorter lifespans (3–5 years). The declining cost of lithium-ion batteries, from $1,100/kWh in 2010 to approximately $132/kWh in recent years, has made battery-based mini-grids more economically viable. In Sub-Saharan Africa, battery storage costs contribute significantly to the total system cost, representing 30%–50% of capital expenditures in solar-battery mini-grids. The integration of advanced battery management systems helps extend battery life and optimize energy dispatch, further reducing costs [7].

IV. DISTRIBUTION INFRASTRUCTURE AND GRID ARCHITECTURE

Mini-grid distribution networks are designed to balance efficiency and cost. Low-voltage AC systems (230V/400V) are commonly used for networks covering distances of up to 5 km, with efficiency losses below 10%. Medium-voltage (11–33 kV) systems are required for longer distances, maintaining efficiency losses below 5% over 20–50 km. Direct current (DC) mini-grids, operating at 48V or 380V, are emerging as a cost-effective solution for reducing conversion losses, particularly in solar-powered mini-grids. In Sub-Saharan Africa, most mini-grids serve small communities with peak loads of 10–500 kW, with some larger installations exceeding 1 MW for commercial and industrial applications.

V. SMART TECHNOLOGIES AND REMOTE MONITORING

The adoption of digital solutions has significantly enhanced the efficiency and financial sustainability of mini-grids. Smart meters enable real-time monitoring, prepaid electricity models, and demand-side management, improving revenue collection and reducing non-technical losses. IoT-based remote monitoring systems track energy generation, consumption, and equipment performance, reducing operational costs and minimizing downtime. In Sub-Saharan Africa, remote monitoring has proven essential in reducing mini-grid maintenance costs by 20%–30% and improving system uptime to over 95%. AI-driven energy management systems optimize load forecasting and resource allocation, further enhancing overall efficiency [8].

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VI. SCALABILITY AND FUTURE INNOVATIONS

Mini-grids in Sub-Saharan Africa are increasingly designed for scalability, allowing incremental expansion based on demand growth. Current installations range from small-scale 10 kW systems serving a few hundred households to large-scale hybrid mini-grids exceeding 1 MW. High-efficiency appliances such as DC-powered refrigerators, water pumps, and fans reduce energy demand, making mini-grids more sustainable. Future innovations, such as blockchain-based peer-to-peer energy trading, have the potential to improve economic sustainability by allowing surplus energy to be sold within mini-grid networks. These advancements, coupled with declining technology costs and supportive policies, position mini-grids as a critical solution for achieving universal energy access in remote and underserved regions [9].

D. THE NEED FOR PLANNING

The successful deployment and long-term viability of mini-grids require comprehensive planning that addresses technical, economic, social, and environmental dimensions [10]. Effective planning ensures that mini-grids are not only technically robust but also tailored to the specific energy needs and priorities of the target communities. This involves careful assessment of local demand patterns, resource availability, and economic conditions to design systems that are efficient, affordable, and scalable. Comprehensive planning also includes integrating mini-grids into broader rural electrification strategies, considering potential future grid interconnections, and aligning with national energy policies and development goals [11].

Additionally, addressing regulatory frameworks, financing mechanisms, and community engagement is essential for fostering local ownership and ensuring the sustainability of mini-grids. Community involvement during planning, construction, and operation helps build trust, encourage responsible energy use, and enhance social acceptance. By adopting a holistic approach that incorporates technical innovations, robust financial models, and inclusive stakeholder participation, mini-grids can play a transformative role in achieving universal energy access and driving sustainable development in rural and underserved areas.

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2. COMPREHENSIVE ENERGY MODELLING FOR MINI-GRID PLANNING

A. INTRODUCTION TO COMPREHENSIVE ENERGY PLANNING

Achieving universal energy access is a central pillar of Sustainable Development Goal 7 (SDG 7) and a prerequisite for sustainable socioeconomic development. However, traditional energy planning approaches, primarily focused on technical and economic optimization, have consistently fallen short in addressing the complexities of energy access in remote and underserved areas. These approaches, while effective in identifying least-cost solutions, often fail to incorporate critical social, cultural, and environmental dimensions, resulting in projects that are technically viable but socially unsustainable or poorly integrated into local contexts.

Comprehensive energy planning is essential because energy systems do not exist in isolation; they are deeply embedded in the socio-economic fabric of the communities they serve. Without understanding the local context—such as community priorities, regulatory frameworks, and behavioral dynamics—projects risk failure, evidenced by cases where systems are abandoned due to lack of engagement, affordability, or technical misalignment with local needs. The challenge is particularly acute in rural areas, where diverse energy demands, geographical isolation, and limited financial resources exacerbate the difficulty of deploying sustainable energy solutions.

Over the past two decades, numerous studies and real-world experiences have underscored the limitations of narrow, techno-economic planning. Research on failed energy projects has revealed recurring issues, such as inadequate community involvement, neglect of socio-cultural factors, and failure to anticipate long-term operational challenges. For example, counterfactual analyses—systematic comparisons between successful and failed projects—have consistently identified gaps in demand assessment, local capacity building, and stakeholder engagement as critical barriers to success.

Frameworks like the **Multi-Tier Framework (MTF)** [12]have expanded the understanding of energy access by emphasizing dimensions such as reliability, affordability, and quality, moving beyond simplistic metrics of availability. Similarly, participatory planning approaches and tools like geospatial analysis have demonstrated the importance of tailoring energy solutions to the unique characteristics of local communities. Business models that integrate financial sustainability with inclusivity—such as cooperative ownership and fee-for-service models—highlight the value of aligning technical solutions with social realities.

As a response to these challenges and insights, the **Comprehensive Energy Solution Planning (CESP)** [10] framework represents a significant evolution in energy access planning. CESP integrates traditional engineering-based methodologies with socio-technical and participatory approaches to create a holistic, iterative planning process. It emphasizes six key phases:

1. **Context Analysis**: Understanding the regulatory, social, and economic environment.
2. **Resource and Demand Assessment**: Evaluating local energy resources and current and future energy needs.
3. **Technical Solution Design**: Identifying and optimizing appropriate technologies for the local context.
4. **Business Model Design**: Developing financially sustainable models that align with local capabilities and needs.

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5. **Complementary Activities**: Supporting initiatives like capacity building, productive uses of energy, and demand-side management.
6. **Impact Analysis**: Monitoring and evaluating project outcomes to ensure alignment with community goals and identify areas for improvement.

B. THE STEPS OF COMPREHENSIVE ENERGY PLANNING

By synthesizing lessons from past projects, CESP addresses the multi-dimensional challenges of energy access, ensuring that energy solutions are not only technically and economically sound but also socially inclusive and environmentally sustainable. This approach transforms energy access projects from isolated technical interventions into integral components of local development strategies, making comprehensive energy planning not just a necessity but a driver of long-term success.

i. Context analysis

Context analysis is a critical step in ensuring that energy access projects align with the unique social, economic, and regulatory environments of the target area. It focuses on two main actions:

1. **Regulatory Framework Assessment**: Understanding the local regulatory environment is essential for designing viable projects. This includes identifying technical, procedural, and economic regulations, such as grid connection standards, permitting processes, and tariff mechanisms. Effective regulatory assessments help identify opportunities and constraints, ensuring projects comply with legal requirements while leveraging available incentives.
2. **Needs and Priorities Identification**: Energy projects must address specific community needs, moving beyond simple measures of energy availability to consider attributes like reliability, affordability, and service quality. Participatory approaches, including stakeholder mapping and problem analysis, facilitate a deeper understanding of community priorities. These insights guide the development of solutions that are not only technically robust but also socially relevant and economically sustainable.

Through a comprehensive understanding of the regulatory landscape and community-specific needs, context analysis provides a strong foundation for designing energy access interventions that are sustainable, inclusive, and impactful.

ii. Resource Assessment

A renewable resource assessment consists in the characterization of the renewable energy resource available for energy conversion at a given location or region over a period of interest, i.e., it is the temporal and geographical quantification of the available energy of a given renewable resource (e.g. wind or Sun). These assessments must be reliable, provide low uncertainty data and account for intra and inter annual patterns and trends of the energy source, which requires the availability of high temporal resolution and long-term data (LEAP-RE Deliverable D13.2).

Renewable resource assessments provide valuable information for different stages of a renewable energy project life-cycle, including: pre-feasibility and feasibility studies, plant/system design, project due diligence and acceptance and plant/system operation and management. The requirements of the resource assessment depend on the intended use of the data. For example, a plant or system design require data with less uncertainty and higher temporal and spatial resolution than for a pre-feasibility study.

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Wind power assessments for mini-grid applications focus on the wind speed and direction at a given height above the ground. Solar resource assessments for mini-grid applications focus in one or several of the components of the solar irradiance[1] or irradiation[2] impinging Earth's surface, namely:

- Global horizontal irradiance (irradiation): the irradiance (irradiation) on a horizontal surface;
- Direct normal irradiance (irradiation): the irradiance (irradiation) on a surface perpendicular to the Sun's rays emanating from the solar disk and the circumsolar region;
- Diffuse horizontal irradiance (irradiation): the irradiance (irradiation) on a horizontal surface resulting from solar radiation scattered and reflected by the air, clouds and other particles in the atmosphere.

In addition to the previously mentioned parameters with the greatest impact on wind and solar power, it is also crucial to characterize other relevant meteorological factors, such as air temperature, humidity, and atmospheric pressure. These factors can influence the efficiency of solar panels, wind turbine performance, and the overall energy output. Properly accounting for these variables helps reduce uncertainties in power generation models and improves the accuracy of energy estimates.

In general terms, the data sources for solar and wind resource assessments can be divided into three categories:

- Ground measured data;
- Satellite derived data (mainly for the solar case);
- Reanalysis data from numerical weather prediction (NWP) models.

Ground measured data is obtained from ground stations equipped with pyranometers and/or pyrheliometers (for solar resource assessments) or anemometers and wind vanes (for wind resource assessments), having high degree of accuracy and high temporal resolution. However, the spatial resolution of this type of dataset is limited, as data is only representative of the station location, moreover, it has high maintenance requirements and is more expensive. Therefore, it is recommended to strategically install measurement stations, particularly in regions with high potential for renewable energy generation and that are representative of the surrounding area. List of ground-based databases publicly available with data for African countries are available in (LEAP-RE Deliverable D10.2).

Satellite derived data can be used for solar resource assessment. In this case, solar irradiance data is derived from remote sensing data provided by satellite imaging and radiometric sensors according to atmosphere radiative models. The main datasets cover all locations on Earth between latitude 60ºN and 60ºS, a latitude band that encompasses the African continent. Solar resource assessment from satellite data presents high temporal resolutions (sub-hourly), high spatial resolution (pixels sides with 10 km up to 1 km. Moreover, long-term data is also available. However, satellite derived data presents higher uncertainties than ground-measured data and in some situations fails to capture in a suitable way the solar variability, particularly under highly fragmented clouded skies. Therefore, it is a best practice the validation of these datasets against ground-measured data, even if only for short periods. Ground-based data, obtained through pyranometers or pyrheliometers, typically has lower uncertainty and higher accuracy, making it a valuable reference. In this case, a blending dataset

[1] Rate at which radiant energy is incident on a surface per unit area of that surface [W/m^2]
[2] Incident energy per unit area of a surface [J/m^2]

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considering a hybrid approach that combines both satellite and ground-measured data can be employed to reduce uncertainties.

In cases where ground measured data is not available for the region of interest, data from other locations with similar climatic conditions can be used as a proxy to identify the most adequate satellite derived dataset. The main satellite-based databases publicly available that provide information covering the African continent are available in (LEAP-RE Deliverable D13.2).

Reanalysis data combine meteorological observations and numerical weather prediction (NWP) models to obtain a long-term retrospective estimation of many atmospheric and climatic variables such as humidity, clouds composition, temperature, wind and radiation properties in a uniform spatial grid with a certain resolution. The use of reanalysis data for wind or solar resource assessment presents as advantage the availability of a uniform grid data for the entire world, temporally consistent (i.e. without missing data) for long term period (can go back up to 30 years). However, this data has low spatial resolution (the highest, from ECMWF's ERA5 has a grid of 0,28º x 0,28º) and limited temporal resolution (typically data is provided with temporal resolution of 1h to 6h). Moreover, reanalysis data only captures a small amount (<60%) of the observed variability in irradiation, being suitable only for analysis of clear sky conditions, and does not account for the effect of aerosols, which can be very relevant for applications using concentrating solar technologies The main reanalysis-based databases publicly available that provide information covering the African continent are available in (LEAP-RE Deliverable D13.2).

To overcome the limitations of this type of dataset, downscaling techniques can be applied to provide location-specific resource estimations. Downscaling enhances the data from global models by incorporating local or regional factors. This can be done using statistical methods that establish relationships between local variables (e.g., solar irradiation) and large-scale variables (e.g., cloud cover). Alternatively, physical approaches based on regional or microscale models tailored to the specific technology being analyzed can also be used for downscaling.

The statistical methods (including machine learning) seek to establish relationships between observed and reanalysis data. In this case, ground based data is necessary. If no observed data is available, physical-based methods based on microscale and/or regional/mesoscale models can be used to obtain a better estimation of renewable resources and overcome the limitations of reanalysis data obtained from global models, which often have low spatial and temporal resolutions. Regional/mesoscale models, such as the Weather Research and Forecasting (WRF) model [13] enable to provide a more detailed description of air mass behavior and evolution with a high spatial resolutions (equal or below 1 km) and temporal resolutions (equal or below 1 hour) and can be calibrated for a specific region. A coupled approach is commonly used, where regional models are initialized and constrained with initial and boundary conditions (IBC) from global models. These IBCs are necessary for the boundaries (boundary, surface, and top of the domain) of the first domain. The IBCs can be sourced from historical data provided by reanalysis projects. Data from reanalysis can also be used in microscale models. These models can provide information with high spatial resolution (10-30 meters). In the case of wind resource linear models, like WAsP, are less computationally demanding and work well for flat terrain but are inaccurate in complex areas, such as hills. Non-linear models, particularly computational fluid dynamics (CFD), offer better accuracy, especially in complex terrains, by incorporating thermal effects and vertical stratification [14], [15]. Studies show that CFD models outperform linear models, especially in periods of extreme wind conditions and power ramps [16].

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Further information on the solar and wind resource assessment and associated databases can be found in previous deliverables from the LEAP-RE project: (LEAP-RE Deliverable D13.2) (LEAP-RE Deliverable D10.2).

Statistical validation methods play a crucial role in ensuring the accuracy and reliability of wind and solar resource assessments. These methods involve comparing model outputs with observed data to identify and correct biases, improve model performance, and provide confidence in the predictions. The most used methods are *i*) common metrics, *ii*) Correlation Analysis and *iii*) Cross-Validation Techniques [17].

The common metrics method uses simple formulation to evaluate the error metric of the predictions. It is based on the calculation of the Mean BIAS Error (MBE) , the Mean Absolute Error (MAE) and the Root Mean Square Error (RMSE). The MBE indicates the average bias in the predictions, showing whether the model tends to overestimate or underestimate the resource. The MAE by their side measures the average magnitude of errors between predicted and observed values while the RMSE provides a measure of the differences between predicted and observed values giving more weight to larger errors. The main strength of the common metrics method is it is simple to calculate and interpret and provide a clear indication of model performance. The main weakness of this method is that it does not provide information on the distribution of errors and can also be influenced by outliers [18].

The correlation metrics measure the linear relationship between predicted and observed values. Commonly used is the Pearson Correlation Coefficient metric in which the value can range from -1 to +1 with +1 indicating the predicted and observed values are totally in phase while -1 indicate a total opposition in phase while a value near zero mean the predicted values are not consistent with observations or the predictions are poor. The main strength of this correlation metric is it is easy to compute and understand while providing insight into the strength and consistency of the relationship between observations and predictions. The main weakness of this method is it can only capture linear relationships and could be misleading if the data contains outliers or non-linear patterns [19].

The Cross-Validation Techniques method utilizes artificial neural networks (ANNs) to model complex relationships between predictions and observations or a Measure-Correlate-Predict (MCP) method to model more simple complex relationships. The ANN is used when predictions and observations are far from linear relationship while MCP can be used when an approximate linear relationship occurs. While ANNs are computationally intensive but capable of capturing non-linear relationships and complex patterns in the data the MCP is more flexible since it captures simple patterns of the data such as the mean daily profile and frequency distribution. Both methods splits the data into k subsets and can be trained k times using different subset as the validation set being the remaining data as the training set. The main strengths of this methods is they provide a more reliable estimate of the model performance by reducing the variance associated with a single train-test split while the main weaknesses of both methods is they can overfitting if non properly adjusted to the non-linearity and therefore require careful implementation to ensure the data is properly rearranged in subsets [20].

The formulas of the common and correlation metrics applied for the solar and wind resource assessment can be found in previous deliverables LEAP-RE Deliverable D13.2 and LEAP-RE Deliverable D10.2 where a set of validation metrics are calculated and evaluated with observational solar and wind data including graphical visualization of the mean daily and mean monthly profiles.

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iii. Load Demand Assessment

Accurate demand estimation is a cornerstone of effective off-grid energy system planning, ensuring that resources are optimally allocated and systems are designed to meet the energy needs of communities reliably and sustainably. This process considers both the current energy requirements and potential future demands driven by socioeconomic development, behavioral changes, and technological adoption. Demand estimation is not merely a technical exercise but a multidimensional task that bridges energy needs with community development objectives LEAP-RE Deliverable D13.2.

Importance of Demand Estimation

Demand estimation is critical for several reasons:

1. **System Sizing**: It guides the appropriate sizing of energy system components such as generation units, storage, and distribution infrastructure. Proper estimation prevents system overload due to under-sizing or resource wastage due to over-sizing.
2. **Cost Optimization**: Accurate demand projections ensure cost-effective allocation of resources, minimizing capital and operational expenses while maximizing system reliability and performance.
3. **Load Dynamics**: Understanding load curves, rather than aggregated energy consumption, is essential for capturing peak demand periods and designing systems capable of meeting these requirements.

Approaches to Demand Estimation

There are several established methods for estimating demand in off-grid contexts, each with strengths and limitations:

1. **Expert-Based Methods**: These rely on assigning predetermined energy consumption values to user categories such as households, schools, and health centers. While practical and widely used, these methods can oversimplify real-world complexities, leading to inaccuracies.
2. **Pre-Defined Load Models**: Tools like HOMER and MicroGridsPy incorporate standard load profiles and allow scenario analysis. These models are valuable for planning but require accurate input data to reflect community-specific energy behavior.
3. **Pre-Electrification Surveys**: Surveys conducted in target communities help identify energy needs and aspirations, as well as current energy expenditures. However, survey data can overestimate demand since respondents may lack experience with modern energy services.
4. **Data-Driven Methods**: These approaches utilize machine learning and publicly available datasets to estimate energy demand, reducing reliance on field surveys. Predictive models based on appliance ownership and usage patterns can generate high-resolution load profiles with limited input data.
5. **Hybrid Approaches**: Combining top-down and bottom-up methods, hybrid models address the shortcomings of each. For example, system dynamics models account for feedback loops between energy access and demand evolution, enabling more accurate long-term projections.

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Challenges in Demand Estimation

Demand estimation faces unique challenges in rural and off-grid contexts:

- **Data Scarcity**: Many rural areas lack detailed data on appliance ownership, energy use patterns, and socioeconomic conditions.
- **Dynamic Evolution**: Energy demand evolves over time as households acquire new appliances and engage in productive uses of energy.
- **Behavioral Complexity**: User behavior, cultural factors, and community aspirations significantly influence energy use, making demand prediction inherently uncertain.

Best Practices for Demand Estimation

To overcome these challenges and ensure robust demand estimation, the following best practices have emerged:

1. **Use of Load Curves**: High-resolution load curves, rather than aggregated metrics, capture peak demand periods and load variability, improving system design.
2. **Community Engagement**: Involving local stakeholders provides insights into energy needs and fosters ownership, enhancing the reliability of demand projections.
3. **Iterative Assessment**: Periodic updates to demand estimates account for changes in community behavior, economic growth, and appliance adoption.
4. **Advanced Tools**: Leveraging data-driven models and geospatial tools reduces dependence on costly field surveys while improving accuracy and scalability.

The Role of Demand Estimation in Development

Proper demand estimation aligns energy access projects with broader development goals, such as improving education, healthcare, and economic opportunities. By identifying and planning for productive uses of energy, such as irrigation, milling, and refrigeration, demand estimation ensures that energy systems catalyze sustainable development.

In conclusion, demand estimation is not only a technical input for energy system modeling but also a strategic process that aligns energy access with long-term community development. Leveraging a combination of methodologies and incorporating local context ensures that off-grid energy systems are both reliable and transformative.

iv. Technical solution design

Introduction

Designing an effective mini-grid system requires precise technology sizing to balance energy supply and demand while optimizing cost, efficiency, and sustainability. The sizing process typically incorporates data-driven modeling, site-specific assessments, and simulation tools. Factors influencing the sizing include load profiles, renewable energy resource availability, demand growth projections, and system reliability. The primary objective is to ensure technical and financial feasibility while taking into account the local socio-economic context. Below is an overview of the key components of mini-grids, their roles, sizing principles, and associated considerations.

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PV Panels

PV panels play a pivotal role in many mini-grid systems due to their scalability, declining costs, and their suitability for off-grid renewable energy generation. They convert solar radiation into electricity, which makes them especially valuable for regions that receive ample sunlight.

The sizing of the PV system begins with an in-depth analysis of daily and seasonal load profiles to ensure that the system generates sufficient energy to meet demand. Solar resource data, such as Global Horizontal Irradiance, is used to assess the potential energy output from the location. System efficiency is also a crucial consideration, with factors such as derating (e.g., temperature losses and dirt accumulation) and inverter efficiency influencing the final sizing.

PV systems are widely favored because they harness renewable energy, are modular, and have relatively low operational and maintenance costs. However, the generation of power is intermittent and dependent on sunlight, which means the system typically requires battery storage or backup systems to ensure reliability during periods of low solar availability.

Other VRES Supply Technologies

Small Wind Turbines

Small wind turbines complement solar PV systems by generating power during periods of high wind, which often coincide with times when solar output is low, such as at night or during winter. The sizing process for wind turbines involves analyzing wind speed and frequency distributions, typically using Weibull probability density functions, to determine how much wind energy can be harnessed to meet the system's needs.

Wind turbines are advantageous in locations where wind conditions are favorable. They can produce energy when solar resources are not available, enhancing the overall reliability of the mini-grid. However, the efficiency of wind turbines is highly site-specific and dependent on the consistency of wind resources. Additionally, wind turbines are maintenance-intensive due to the moving parts.

Pico Hydro

Pico hydro systems harness flowing water from small streams or rivers, offering a continuous and predictable energy source in regions with appropriate hydro resources. Sizing involves calculating potential energy output based on water flow (Q) and head height (H), as well as considering seasonal variations in water availability.

Pico hydro systems are advantageous because they can provide a reliable, low-impact energy source. However, these systems require access to suitable water sources and are vulnerable to changes in water flow, especially during dry seasons or due to sedimentation.

Batteries

Batteries are essential in mini-grids for storing excess energy generated during times of high production for later use during periods of low generation or peak demand. Proper battery sizing involves accounting for daily load profiles, desired autonomy periods, and factors like the depth of discharge (DoD) and efficiency.

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When selecting between battery types, lead-acid batteries are a low-cost option with shorter lifespans and lower energy densities, while lithium-ion batteries, though more expensive, offer higher energy densities, longer lifespans, and better efficiency. Batteries are vital for integrating intermittent renewable energy sources, improving system reliability, and ensuring power availability when renewable generation is insufficient. However, high capital costs, particularly for lithium-ion batteries, and environmental concerns about battery disposal need to be considered.

Diesel Generator

Diesel generators are used in mini-grids as backup or supplementary power sources to ensure the system remains operational during times of high demand or when renewable energy generation is low. The sizing of diesel generators is typically based on the peak load that needs to be supported, ensuring that they can meet demand or supplement renewable generation when necessary.

Generators are most efficient when operating at an optimal load (typically 60-80% capacity), which helps reduce fuel consumption and wear. While diesel generators are reliable and easy to deploy, they incur high operational costs due to their dependency on fuel, and they contribute significantly to greenhouse gas emissions.

Inverters

Inverters are used in mini-grids to convert the DC power generated by PV panels or stored in batteries into AC power for distribution. They also manage power flows between different energy sources and loads, ensuring that the system operates smoothly.

There are several types of inverters used in mini-grids, including centralized inverters for large-scale systems, string inverters for medium-sized systems, and hybrid inverters that can manage inputs from multiple sources, such as solar, batteries, and diesel generators. When selecting inverters, key considerations include their efficiency ratings and their ability to function in off-grid systems, where grid-forming capabilities are often required.

Distribution Line

Designing an efficient distribution system is crucial for mini-grids. Proper planning ensures that voltage drops remain within acceptable limits and that energy losses are minimized through appropriate conductor sizing and material selection. The system must also be resilient to environmental conditions and meet local regulations. Furthermore, distribution systems should be designed with expansion in mind, to accommodate future increases in load as the community's demand for electricity grows.

Effective distribution design ensures that the electricity generated by the mini-grid reaches consumers efficiently, enabling the system to operate reliably and sustainably.

v. Business model identification and formulation

The success and sustainability of mini-grid projects hinge on a well-defined business model. These models serve as strategic frameworks that enable stakeholders to deliver energy services, particularly in underserved areas, while ensuring financial and operational viability. Effective business models align technical and commercial objectives with the socio-economic realities of the communities they serve, making them indispensable for rural electrification and broader energy planning initiatives.

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In energy planning, particularly for rural or off-grid areas, understanding the interplay of ownership structures, financial strategies, and the integration of productive uses of energy (PUE) is crucial. This chapter discusses methodologies for defining business models tailored to the unique challenges of mini-grid systems and offers insights into their integration within broader energy planning frameworks.

Business Model Design

Designing an effective business model requires a nuanced understanding of customer types, their specific energy needs, and financial capabilities. Central to this process is balancing costs with revenue streams, which may include electricity sales, ancillary services, and PUE activities. This section details:

1. **Customer Segmentation**: Identifying and understanding the needs of households, commercial entities, and community users.
2. **Tariff Setting**: Aligning tariffs with the ability and willingness to pay while ensuring the system's financial sustainability.
3. **Partnerships**: Leveraging local and international partnerships for technical, financial, and operational support.

Delivery Model

The delivery model specifies how a mini-grid system is established, operated, and maintained. Key considerations include asset ownership, operational responsibilities, and financing structures. Depending on project goals, delivery models may range from government-led utility models to public-private partnerships or community-driven cooperative models.

Incorporating Productive Uses of Energy

PUE can significantly enhance the financial and social impact of mini-grids by fostering economic development in rural areas. Strategies such as the Anchor-Business-Consumer (ABC) model, diversified customer bases, and business acceleration approaches are explored to integrate PUE effectively into mini-grid operations.

Strategic Approaches to Inclusivity and Cost Reduction

Inclusivity and cost efficiency are critical for the sustainability of mini-grids. Inclusive strategies involve community participation in value creation and capture, including training programs, revenue-sharing mechanisms, and entrepreneurial support. Simultaneously, innovative cost-reduction methods, such as clustering and containerized solutions, are evaluated for their applicability in different contexts.

Tariff Setting: Balancing Affordability and Viability

Tariff structures should reflect the cost of service delivery while remaining accessible to end users. The chapter outlines approaches to design tariffs that encourage energy efficiency, align with regulatory frameworks, and incorporate smart metering technologies.

Tools for Business Model Development

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To assist planners and developers, tools like the Business Model Canvas, Value Proposition Canvas, and Lean Startup Canvas are highlighted for their ability to streamline the development and evaluation of business models. These tools offer structured methodologies to align business objectives with customer needs and operational realities.

Conclusion

Integrating robust business models into mini-grid planning ensures the technical, financial, and socio-economic success of energy projects. By emphasizing inclusivity, innovative financing, and strategic partnerships, planners can develop mini-grids that not only electrify but also empower communities.

vi. Complementary Activities and Impact analysis.

Complementary Activities for Long-Term Sustainability

Energy access alone does not guarantee community development; it must be supported by complementary activities tailored to local needs. These activities ensure that the economic, social, and environmental benefits of energy access are fully realized. Complementary measures can include:

1. **Productive Use Enablement**: Providing microcredit schemes or financing for energy-efficient appliances can stimulate local businesses and boost demand for electricity.
2. **Capacity Building**: Training programs for local technicians and operators promote employment and ensure the sustainability of mini-grid operations.
3. **Market Development**: Facilitating access to local and regional markets ensures that economic gains from energy access are reinvested into the community.
4. **Institutional Support**: Strengthening local governance and cooperative models ensures that benefits are equitably distributed and long-lasting.

These measures are particularly impactful when managed at the local level, such as through cooperatives that reinvest electricity revenues into community projects. This approach aligns individual and community goals, optimizing resources and fostering long-term sustainability.

Impact Assessment: Monitoring and Evaluation

To gauge the success of mini-grid projects, comprehensive impact assessments are vital. These evaluations examine the effects of interventions across economic, social, and environmental dimensions, ensuring that projects deliver on their objectives while identifying areas for improvement.

Key components of impact assessment include:

1. **Baseline Studies**: Establishing benchmarks against which to measure project outcomes, including energy access rates, local income levels, and environmental conditions.
2. **Result Chain Framework**: Utilizing tools like the Logical Framework to link project inputs to outputs, outcomes, and long-term impacts
3. **Causal Analysis**: Identifying and verifying relationships between interventions and observed impacts, often employing methodologies like counterfactual analysis to determine what would have occurred in the absence of the project

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Data quality and availability are critical challenges in impact assessments. Innovative solutions such as leveraging large datasets from advanced metering infrastructure or employing control trials can enhance the reliability of evaluations. Regular feedback loops from these assessments inform iterative improvements in project design, ensuring alignment with community needs and sustainability goals.

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3. MATHEMATICAL REPRESENTATIONS OF OFF GRID ENERGY SYSTEMS

A. ENERGY SYSTEM MODELLING

Energy modeling is a fundamental approach to understanding, planning, and optimizing energy systems. It involves employing various software platforms to simulate, analyze, and interpret energy data and scenarios. These tools empower researchers, decision-makers, and industry experts to navigate complex energy challenges, evaluate the implications of diverse strategies, and inform key decisions. In this section, we review commonly used tools for modeling energy systems at the community scale, with their key features compared in Table 1.1. This comparison highlights aspects such as software accessibility (commercial vs. non-commercial), the presence of a Graphical User Interface (GUI), the ability to store or generate energy input data automatically, support for renewable energy sources, capacity for multi-year and multi-energy analyses, and grid interconnection capabilities.

HOMER (Hybrid Optimization of Multiple Energy Resources) is a widely recognized tool for analyzing distributed energy systems and microgrids. It optimizes system configurations by incorporating various generation technologies, storage options, and demand profiles. Operating strategies such as Load Following, Cycle Charging, and Predictive methods are implemented, along with multi-year simulation capabilities and integration of thermal demand. However, its network capabilities are limited to grid interconnection. HOMER includes automatic parameter loading features but is proprietary, requiring a license fee after a trial period.

Other tools, such as DER-CAM and iHoga, were developed for microgrid sizing in academic settings but are not open-source. In contrast, open-source tools like MicroGridsPy and similar software have emerged from academic initiatives, focusing specifically on optimizing microgrids. Their open-source nature facilitates collaboration within the scientific community to tackle challenges such as demand evolution, multi-objective optimization, and stochastic modeling. Additionally, these tools are free, making them particularly valuable for institutions in developing regions.

There are also versatile energy models not designed exclusively for microgrids but adaptable to their analysis due to flexible geographic resolution and scope. RETScreen, for instance, offers heuristic-based economic and environmental evaluations with preset values. It supports renewable energy integration, storage, and multi-year analysis but provides limited network modeling. EnergyPlan, developed by Aalborg University, is an open-source tool designed to optimize integrated energy systems, accounting for various energy sources, demand patterns, and environmental constraints. It also features a user-friendly graphical interface.

PyPSA (Python for Power System Analysis) is an open-source library that supports power system analysis and optimization, including renewable energy and storage integration. Similarly, Calliope is an open-source framework for modeling and optimizing energy systems across different scales, from local to national. It enables multi-energy carrier integration and decarbonization pathway exploration, albeit with a simplified representation of electrical networks.

While tools with graphical interfaces may be more accessible to users with limited programming skills, open-source platforms offer greater flexibility and customization for those with basic coding experience. Although commercial tools often provide structured support services, open-source

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projects have proven responsive and offer robust community-driven support, along with other significant benefits.

Table 1 – Well Known Microgrid Optimization Models

Modelling Tool	Open-Source	GUI	Optimization	System Operation	Multi-year	Multisectorial	National Grid	REF
Homer	No	Yes	Heuristic	Load Follow, Cycle Charging, Perfect Forsight	Limited	Yes	Yes	[21]
MicroGridsPy	Yes	Yes	MILP	Perfect Forsight	Yes	Yes	Yes	[11]
matMicrogrid	Yes	No	Hybrid	Load Follow, Cycle Charging, Perfect Forsight	Yes	No	No	[22]
multi-objective	Yes	No	MILP	Perfect Forsight	Yes	No	No	[23]
iHoga	No	Yes	Heuristic	Load Follow, Cycle Charging	Yes	Yes	Yes	[24]

The tools discussed offer a wide range of functionalities for energy modeling, such as scenario exploration, optimization, and sensitivity assessment. They facilitate the analysis of alternative energy strategies, policy evaluation, and the examination of trade-offs among various components of energy systems. While these tools determine the optimal sizing of system components, it is ultimately the developer’s responsibility to choose compatible devices and design a control system capable of ensuring the system's stability.

B. MATHEMATICAL OPTIMIZATION TECHNIQUES

Optimizing an energy model consists in the execution of specific algorithms aimed to identify the value of variables that minimizes or maximizes a target objective function subject to satisfying a set of constraints specific to the problem [25]. Various techniques are available and their suitability depends on the mathematical formulation of the problem [26]. In this section, we denote the basics of the mathematical techniques suitable for optimizing energy systems.

First, the key elements in mathematical optimization are the notions of parameters, variables, expressions, constraints and objective function [26], [27]. Parameters are numerical values known a-priori before the execution of the algorithm and accordingly are not a result of the optimization algorithm. An example is the specific investment cost for each asset of the system. Variables are quantities determined by the optimization process, they are varied – respecting the given constraints

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- in order to identify the minimum or maximum value of the objective function, when it exists, and therefore are the main decision-making elements in the optimization problem. Variables x can be of various types, continuous real numbers $x \in \mathbb{R}^N$, semi-continuous real numbers e.g. non-negative values $x \in \mathbb{R}_0^N$, integer $x \in \mathbb{Z}^N$ or binary $x \in \{0,1\}^N$. The type of variable has significant implications into the complexity of the problem, optimization technique and feasibility of the solution. Indeed, when integer or binary variables are considered, the problem is intrinsically non-convex as it is represented by the combination of values of binaries and integers whose computational costs scale exponentially with the size of the problem. Expressions are instead mathematical functions expressed in terms of existing variables and parameters. The most basic representations are linear expressions that can be represented as $f(x) = c^T x = c_1 x_1 + \cdots + c_n x_n$, where c is a vector of parameters and x a vector of variables, and the problem is defined as "linear programming" (LP) problem. However, mathematical problems may be described also by non-linear expressions $f(\cdot): \mathbb{R}^N \to \mathbb{R}^M$ and in such cases, the algorithmic complexity increases, and the problem ceases to be linear. Typical classes of functions are: linear, quadratic, convex non-linear and non-convex non-linear. Convex expressions ensure convergence to the global optimum when an appropriate solver is adopted [26], whereas non-convex formulations have no convergence proof and they require more specialized algorithms. Linear $(c^T x)$ or $(c^T x + d)$ affine expressions are the simplest form of expressions and they are convex. Quadratic expressions $(x^T Q x)$ are special formulations, heavily studied in the literature with specialized algorithms and they fall into the convex category, with appropriate characteristics of Q. Finally, each mathematical model is described by constraints that are generally equality or inequality terms in the form $g(x) \geq 0$, $g(x) \leq 0$ or $g(x) = 0$, where $g(\cdot): \mathbb{R}^N \to \mathbb{R}^K$ denotes any mathematical expression previously defined.

Note that, in mathematical terms, given the preliminary notions, a general optimization problem can be described as in (1) [26]:

$$\begin{aligned} & min. f(x) \\ s.t \quad & g(x) \leq 0 \\ & x \in \Omega \end{aligned} \tag{1}$$

The mathematical problem denoted in (1) represents a minimization problem of the function f subject to a series of constraints represented by the function $g(\cdot)$ in the domain $x \in \Omega$ that can represent any variable type. Note that with no loss of generality we represented the inequality constraint $g(x) \leq 0$ that can formally represent other equality and inequality constraints. For example, we can represent equality constraints $g'(x) = 0$ by defining $g(x) = \begin{bmatrix} g'(x) \\ -g'(x) \end{bmatrix} \leq 0$: the constraints ensures that $g'(x)$ must be non-negative and non-positive hence collapsing into the equality constraint. Depending on the characteristics of the domain of the variables Ω and the characteristics of the objective function $f(\cdot)$ and constraints $g(\cdot)$, the complexity of the mathematical problem, its execution time and computational resources can vary significantly.

In the following, we clarify the notation for the most common class of mathematical problem for microgrid optimization that entails linear expressions for $f(\cdot)$ and $g(\cdot)$, combined with continuous, semi-continuous and/or integer/binary variables. This class is also known as Mixed-Integer Linear Programming (MILP) or Linear Programming (LP) [27], whether integer $(x_j \in \mathbb{Z})$ or binary $(x_u \in \{0,1\})$ variables are included or not, and their mathematical form is denoted as in (2):

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$$
\begin{aligned}
& \qquad\qquad min.\ c^T x \\
s.t \qquad & \qquad\quad A\,x \leq b \\
& x_i \in \mathbb{R}, \qquad i \in I \\
& x_j \in \mathbb{Z}, \qquad i \in J \\
& x_u \in \{0,1\}, \qquad u \in U
\end{aligned}
\tag{2}
$$

In microgrid optimization, the objective function $c^T x$ typically denotes economic interests, as better detailed in the following section, whereas the constraint $A\,x \leq b$ compactly defines the technical energy modelling of the network. For example, the constraint accounts for maximum and minimum power and energy limitation of the energy assets, as well as energy balances. The equivalence of the formulation with respect to (1) is achieved by defining $g(x) = A\,x - b \leq 0$. Depending on the interest of the developer, variables x can represent the power dispatch of the assets and/or the new installed capacity of the assets. (Mixed-Integer) Linear Programming is a widely studied research topic and a large variety of solvers are currently available, be them open-source or freeware, such as GLPK [28] or HiGHS [29], or commercial ones, such as Gurobi [30], CPLEX [31], or XPRESS [32].

Formulation in (2) is widely adopted and denotes the de-facto standard in energy modelling. However, when the modelling of the system contains any non-linear expressions in (1), the corresponding problem becomes non-linear, which requires more advanced mathematical solvers.

Given the mathematical description of the problem, be it in the general form (1) or in the special (MI)LP case in (2), a series of methodologies are available to solve them, classifiable in the following:

1. Enumerative techniques, or exhaustive search: These methods, often referred to as "brute-force" approaches, explores every combination of system configurations, including layouts and component sizes within a predefined set of choices, calculate the target objective function, and select the optimal variables' values as those that perform best according to the target objective. Simulations are used to estimate the profitability of each configuration, and the one with the lowest cost is selected. These techniques support linear and non-linear formulation and achieve the global optimum within the selected size configurations, pre-loaded by the user. While it is an effective approach for finding the best solution, these techniques are only practical for relatively small sets of options, otherwise their combinatorial nature makes the computational burden extreme. They are widely adopted by various tools, such as HOMER [21].
2. (Meta-)Heuristic algorithms: (Meta-)Heuristic algorithms are algorithmic techniques, generally inspired by dynamics in natural systems, designed to find near-optimal solutions for complex problems [33], [34]. Well-known examples of these algorithms are Genetic Algorithms, which emulate the reproduction and mutation of DNA, or Particle Swarm Optimization, which simulates the behavior of swarms in collecting food. Unlike exact optimization techniques that guarantee achieving the best solution, heuristics focus on practicality, leveraging simplified rules and strategies to produce satisfactory results, especially for problems where exhaustive search or mathematical optimization is computationally infeasible. They can be adopted for both non-linear and linear problem formulations. Under specific circumstances, they may achieve the global optimum, yet it is not guaranteed to be achieved nor there are estimates in the accuracy of the result, contrary to other techniques.
3. Mathematical Programming algorithms [26], [34]: Mathematical programming describes a broad range of techniques that employs specific mathematical-proven algorithms to solve

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specific class of mathematical problems in standard form, such as LP and MILP. These methods aim to find the best possible solution, often subject to constraints, by formulating problems as optimization models. Various algorithms are adopted depending on the type of mathematical programming technique. The most common types of mathematical programming techniques include Linear Programming (LP), Non-Linear Programming (NLP), and Mixed Integer Linear Programming (MILP), each suited to different types of problems and requirements. For microgrid optimization, where LP or MILP are most common, typical solver relies on algorithms like Simplex, Barrier methods or Interior Point methods and variants.

C. OPTIMIZATION MODELLING FRAMEWORKS

Figure 1 reports the standard procedure to model and optimize specific energy systems. The core of the process is the energy modelling framework, typically a software tool for the mathematical representation of the energy system. To successfully deploy the mathematical equations to correctly formulate an optimization problem, the energy framework generally relies on an optimization modelling language or library (e.g. pyomo [27], PULP [35], AMPL [36], cvxpy [37], GAMS [38], among others) that is specifically designed to craft mathematical optimization problems based on variables, expressions, objective and constraints as denoted in the previous section. The optimization framework lays the groundwork for computational solvers to then explore and optimize the problem. Indeed, the energy framework employs the mathematical framework to describe the mathematical formulation of the desired energy system and then it launches the optimization. The optimization is generally performed by a third software referred to as "solver", such as highs [29], glpk [28], gurobi [30] among others.

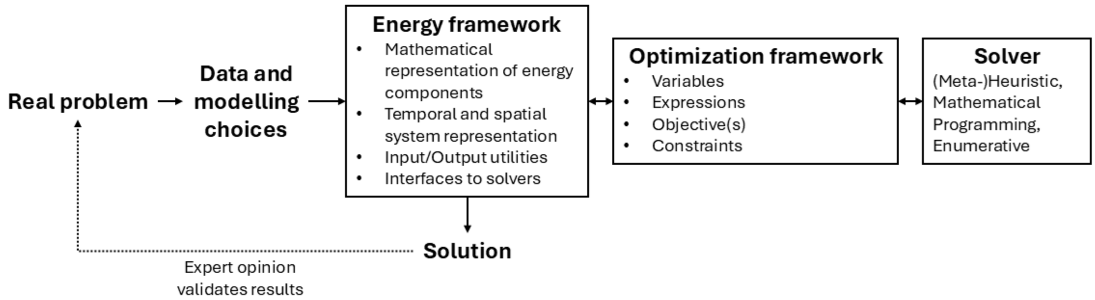

Figure 1 - Optimization modelling in microgrids

In order to represent a specific energy system within an energy modelling framework, the appropriate data that characterize the real problem have to be fed to the model, alongside information to properly setup constraints and objective functions, such as the point of view of the stakeholders. Data and the stakeholders' opinions allow to successfully characterize the real problem and hence develop the corresponding energy model. An energy model, being an object able to represent a system, is indeed an energy framework populated with data [39]. The data that need to be fed to the framework to characterize the energy system include: the type and numerosity of components, their energy characteristics including efficiencies and nominal ratings, capital and operational costs, as well as the final demand and availability of renewable sources. The energy framework stores the information and feeds the optimization framework to successfully develop and optimize the mathematical model of the system. Once the solution is achieved, finally, the expert that is executing the optimization validates the result.

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The optimization framework is a software tool or programming language that allows to define the problem in a structured way, defining it in terms of variables, expressions, objective function(s) and constraints in a format compatible with solvers. The mathematical framework lays the groundwork for computational solvers to explore and optimize the problem. The benefit of optimization frameworks is their ability to allow a simple development of optimization problems, abstracting from the specific model interfaces, while also supporting multiple solvers. Similarly to solvers, a large variety of optimization frameworks are available supported on various software programming languages with different licenses (commercial and open-source). The most notable ones are:

- **Pyomo** [27]: Pyomo is a Python-based, open-source optimization modeling language that allows users to define variables, objectives, and constraints in a highly flexible manner. It supports a wide range of solvers and is particularly suited for large-scale optimization problems, including linear, nonlinear, and mixed-integer programming.
- **Linopy** [40]: Linopy is a Python library designed to solve linear and mixed-integer optimization problems in a structured and user-friendly way. It is particularly useful for energy system modeling and other resource allocation problems that require linear programming techniques.
- **PULP** [35]: PULP is a simple and intuitive Python library for linear programming. It is widely used for smaller-scale optimization problems and offers built-in solvers, along with the ability to interface with external solvers like CPLEX and Gurobi. Its lightweight nature makes it an excellent choice for beginners or straightforward applications.
- **CVXPY** [37]: CVXPY is a Python library designed for convex optimization problems. It provides a user-friendly interface for defining optimization models with a focus on convex objectives and constraints. CVXPY is ideal for problems in machine learning, finance, and energy optimization that require robust solutions under convex assumptions.
- **JuMP** (Julia for Mathematical Programming) [41]: A open-source domain-specific modeling language embedded in Julia, JuMP is known for its speed and flexibility. It supports linear, nonlinear, and mixed-integer programming and interfaces seamlessly with many solvers.
- **AMPL** (A Mathematical Programming Language) [36]: AMPL is a commercial optimization modeling language designed for high-level mathematical programming. It provides a concise syntax for defining optimization problems and can work seamlessly with numerous solvers. AMPL is known for its efficiency in handling large and complex models, particularly in industry-scale applications.
- **GAMS** (General Algebraic Modeling System) [38]: A high-level modeling system for mathematical programming problems, GAMS is designed for large-scale and complex problems. It supports a wide variety of solvers and is widely used in academia and industry. GAMS is a commercial software that requires paid license.
- **YALMIP** (Yet Another LMI Parser) [42]: YALMIP is a MATLAB-based modeling toolbox for optimization problems. It provides a high-level interface to formulate optimization problems, including linear, nonlinear, and semidefinite programming. YALMIP supports a wide variety of solvers and is particularly popular in control systems, robust optimization, and signal processing research. Its flexibility allows users to focus on problem modeling without being constrained by solver-specific syntax, making it an excellent choice for academic and applied research. While YALMIP is easily available, it requires MATLAB that is a licensed commercial product.
- **IBM ILOG CPLEX Optimization Studio** [31]: IBM ILOG CPLEX Optimization Studio is a comprehensive optimization commercial software suite designed for modeling and solving

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complex mathematical programming problems. The studio provides a modeling environment through its Optimization Programming Language (OPL) and integration with Python and other programming languages.

Existing optimization frameworks extensively support a large variety of modelling features and interface. To clarify key differences among optimization frameworks and their usability for energy modelers, **Error! Reference source not found.** summarizes the main differences and similarities across optimization modelling frameworks. The tables depicts key technical and usability features: licensing, software language and supported technical tools, alongside examples of how to initialize the optimization model, create variables, expressions, constraints and objective functions. Overall, state-of-the-art mathematical frameworks are generally similar from a technical and usability perspective. Commercial tools may offer advanced modelling features and optimized techniques, yet at the cost of paid license. On the other hand, open-source free alternatives are still available and easy to use, hence supporting the development of energy modelling tools as described in the following sections.

Table 2 – Optimization Frameworks

	Pyomo	**linopy**	**CVXPY**	**JuMP**	**GAMS**
Licensing	Open-Source	Open-Source	Open-Source	Open-Source	Commercial
Language	Python	Python	Python	Julia	GAMS Language
Supported models	Linear, Nonlinear, Mixed-Integer	Linear, Nonlinear, Mixed-Integer, Convex	Linear, Mixed-Integer, Convex	Linear, Nonlinear, Mixed-Integer, Convex	Linear, Nonlinear, Mixed-Integer
Create Model	from pyomo import * model = ConcreteModel() or model = AbstractModel()	from linopy import Model model = Model()	import cvxpy as cp	using JuMP model = Model()	Model model … ;
Creating Variables	model.x = Var(bounds=(0, 10))	model.add_variables(lower=0, upper=10)	x = cp.Variable()	x = @variable(model, 0 <= x <= 10)	Variables: x(lo, hi); e.g., x(0, 10)
Creating Expressions	model.expr = Expression(expr=model.x + 2 * model.y)	expr = model.add_expression(x + 2*y)	expr = x + 2 * y	expr = @expression(model, x + 2y)	expr = x + 2*y
Defining Constraints	model.con = Constraint(expr=model.x + model.y <= 20)	model.add_constraints(x + y <= 20)	constraints = [x + y <= 20]	@constraint(model, x + y <= 20)	Equations: con.. x + y =L= 20
Defining Objective	model.obj = Objective(expr=model.x + model.y, sense=minimize)	model.add_objective(x + y, sense="min")	objective = cp.Minimize(x + y)	@objective(model, Min, x + y)	Equations: obj.. x + y =E= Z solve model using lp minimizing obj
Solver Invocation	SolverFactory('glpk').solve(model)	model.solve(solver_name='highs')	problem = cp.Problem(objective, constraints); problem.solve()	optimize!(model)	solve model using lp minimizing obj
Reference	[27]	[40]	[37]	[41]	[38]

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4. MINI-GRID OPTIMIZATION CASE STUDY

This chapter presents a detailed case study on the optimization of a mini-grid system, applying state-of-the-art energy modeling and optimization techniques in an African context. The case study focuses on the mini-grid in Faza, Kenya, providing a comprehensive assessment of system design, capacity planning, and performance evaluation under different scenarios. The case study slelected is an existing diesel minigrid in Faza, a community on Pate Island in Lamu County, Kenya. The analysis explores the local minigrid system established in 2017. Faza comprises seven villages, home to around 17,540 residents in 3,453 households. Approximately 3,800 residents were connected to the microgrid at the time of the data collection campaign in 2022 [43]. The microgrid system features two diesel generators providing a total installed capacity of 900 kW, operated by Kenya Power and Lighting Company (KPLC). The main objective of this case study is to showcase the potentiality of use of an open-source energy model, optimizing the hybridization of the minigrid with renewable power sources, evaluating various configurations and operational strategies. The optimization is carried out using MicroGridsPy [11], an open-source modeling framework that employs Mixed-Integer Linear Programming (MILP) to optimize system configurations. This tool is integrated with detailed cost and resource data to simulate the long-term performance of the mini-grid under different assumptions.

A. DEMAND DATA

To evaluate future electricity demand, energy usage data from 2022 was aggregated into an hourly dataset [44]. Projections considered both the increase in households connected to the microgrid and the transition to higher appliance tiers by connected households.

Estimation of Household Connections

Household connections were estimated using historical data and projected growth scenarios. Initially, 748 households were connected to the microgrid (Table 3). Historical growth was adjusted, and future connections were projected under high, moderate, and low growth scenarios. The average annual rate of change was calculated to project future connections over a 20-year period.

Table 3 – Household Connections in Faza. Sampled and Village Adjusted

Year	Sample Household Connections	Adjusted Household Connections
2017	42	209
2018	96	479
2019	123	613
2020	141	703
2021	150	748

The new connections are estimated in three different scenarios (Figure 2).

- High Scenario: 50% of the average historical rate of change.
- Moderate Scenario: Equal to the average historical rate of change.
- Low Scenario: 150% of the average historical rate of change.

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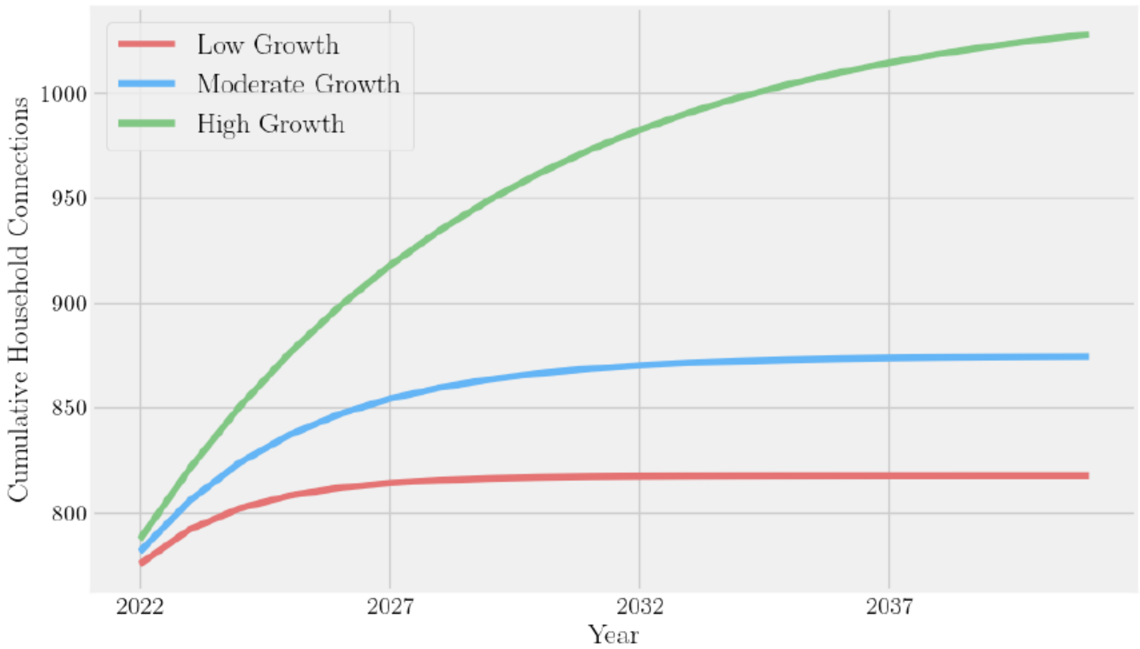

Figure 2 – Cumulative Household Connections in the three scenarios.

Yearly Average Appliance Tier Calculation

Appliance tiers evolution were estimated using a logistic growth function for early and late adopters. The average appliance tier for each year was calculated considering the adoption ratio and growth scenarios (Table 4). The results underscored the potential transition in appliance usage over time [45].

Table 4 – Tiers Characterization

Tier	Cost	Electricity Use	Appliances
1	Very low or low	Very low	Light bulbs, Mobile phones
2	Low	Low	Fan, TV, Speakers, MP3, Radio
3	Moderate	Low or moderate	Blender, Iron box, Electric kettle, Pressure cooker, Donut maker, Microwave, PC, Printer, Wi-Fi router
4	High	Moderate or high	Water pump, Oven, Heating, Fridge, Three appliances from Tier 3
5	High	High	At least two from Tier 4 or four appliances

The yearly appliance tier for each group, scenario, and year of connection was calculated using a logistic function calibrated on observed trends, to estimate the following 15 years of microgrid operation as described in [46] (Figure 3).

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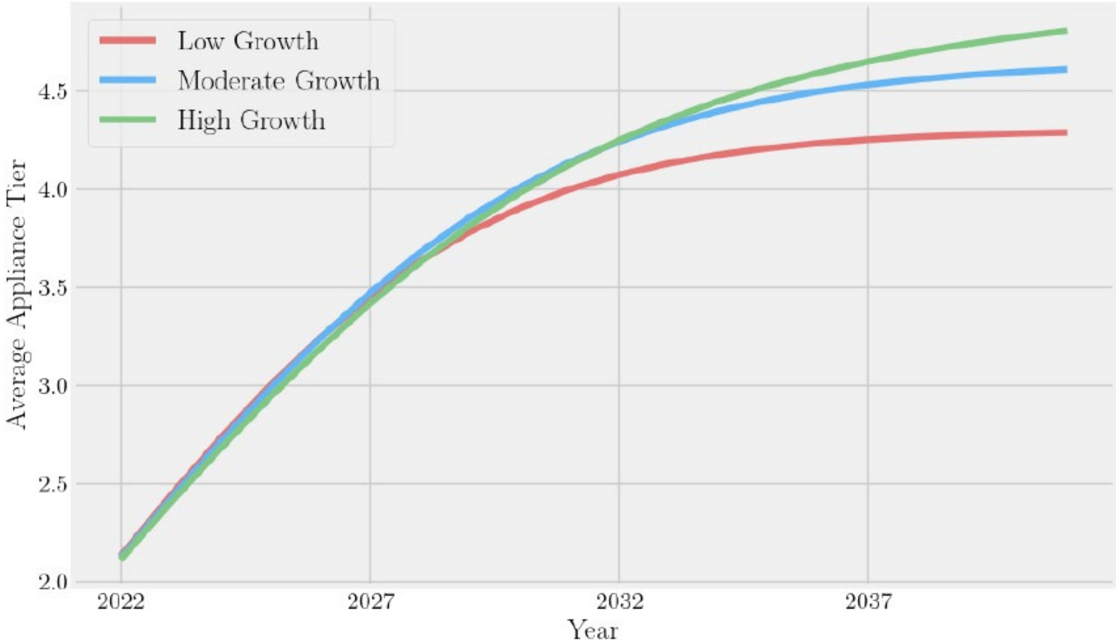

Figure 3 – Appliance Tier evolution of Households in Faza in the three scenarios.

Estimation of Household Connections

Future electricity demand was approximated by considering the growth in connected households and appliance tiers. Using a regression factor, the annual demand increase was calculated, leading to projections of future demand across low, moderate, and high growth scenarios.

B. COST DATA

Cost of Renewable Energy Sources (RES)

Cost estimates for solar PV and batteries were based on actual price data from Kenya and future projections from NREL. Wind energy costs were directly taken from NREL data due to the lack of local data. Future costs were projected under conservative, moderate, and advanced scenarios.

Future Diesel Price

Future diesel prices were projected using historical data from Kenya's EPRA and IEA scenarios. The IEA scenarios include:

- **450 Scenario**: Pathway to limit global warming to 2°C.
- **Current Policies Scenario**: Future based on current policies.
- **New Policies Scenario**: Includes announced but not yet implemented policies.

Prices were estimated by linking local diesel to global oil prices, calculating a diesel-to-oil price ratio, and interpolating future oil prices for 2025 to 2041.

C. RESOURCE AVAILABILITY DATA

Resource data for solar radiation, temperature, and wind speed were obtained from PVGIS TMY, combining satellite-based observations and reanalysis data to reflect average climatic conditions.

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D. SCENARIO SETTING

Three sensitivity analyses were conducted to evaluate the impact of demand growth, technology costs, and system architecture. Each analysis targeted specific aspects, such as varying demand growth scenarios, RES cost projections, and different system configurations (Table 5).

Table 5 – Scenarios Definition

Scenario	Parameters	Key Variations
Demand Sensitivity	Moderate technology costs, Current Policies for fuel prices, AC microgrid with DC subsystem	Low demand growth, Moderate demand growth, High demand growth
Technology Cost Sensitivity	Moderate demand growth, AC microgrid with DC subsystem	Best Case: Low RES cost, high diesel price, Base Case: Moderate projections, Worst Case: High RES cost, low diesel price
Architecture Comparison	Moderate scenario for all parameters, AC microgrid, AC microgrid with DC subsystem	DC Subsystem Architecture: Solar PV is connected to the same inverter as the battery, building a DC subsystem, No DC Subsystem Architecture: Solar PV has its own inverter

E. RESULTS – DEMAND SENSITIVITY

In this subsection, the impact of varying energy demand on capacity allocation and economic performance is analyzed. Table 6 and Figure 4 present the system sizing results, conducted with the open-source software MicroGridsPy [11]. The installed capacities of renewable energy sources (RES) and supporting technologies increase proportionally with rising demand. This trend is especially evident in the scaling of solar PV and battery storage capacities, which adjust to meet increasing energy needs.

Solar PV capacity steadily increases across all demand scenarios, reflecting its modular nature and adaptability to varying demand levels. Battery storage also expands significantly to balance supply and demand and manage peak loads. However, wind turbines and diesel generators exhibit stepwise increases due to their high fixed unit sizes, 100 kW for wind turbines and 450 kW for diesel generators.

Regarding economic impact, the Levelized Cost of Energy (LCOE) shows a decreasing trend from 19.64 USD/kWh in the Low Demand scenario to 19.25 USD/kWh in the Base Case, further dropping to 18.77 USD/kWh in the High Demand scenario. Although this decreasing LCOE with rising demand might suggest economies of scale, technology costs remain constant regardless of installed capacity. The lower LCOE in higher demand scenarios is driven by the timing of RES installations over the project's lifespan. In higher demand growth scenarios, a larger share of the total installed capacity is added in later stages of the project, aligning with increasing energy needs and taking advantage of lower renewable energy prices.

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Table 6 – Demand Sensitivity Results

Technology	Scenario	Existing	Step 1	Step 2	Step 3	Step 4	Total
Solar PV (kW)	Low Demand	0	1170	446	551	367	2534
	Base Case	0	1185	497	830	569	3081
	High Demand	0	1202	580	1108	1009	3899
Wind (kW)	Low Demand	0	0	200	0	0	200
	Base Case	0	0	300	0	0	300
	High Demand	0	0	300	0	0	300
Diesel Generator (kW)	Low Demand	900	0	0	0	450	1350
	Base Case	900	0	0	0	900	1800
	High Demand	900	0	0	450	450	1800
Battery (kWh)	Low Demand	0	5311	2520	2528	1825	12184
	Base Case	0	5355	2946	3747	2738	14786
	High Demand	0	5403	3259	5269	4682	18613

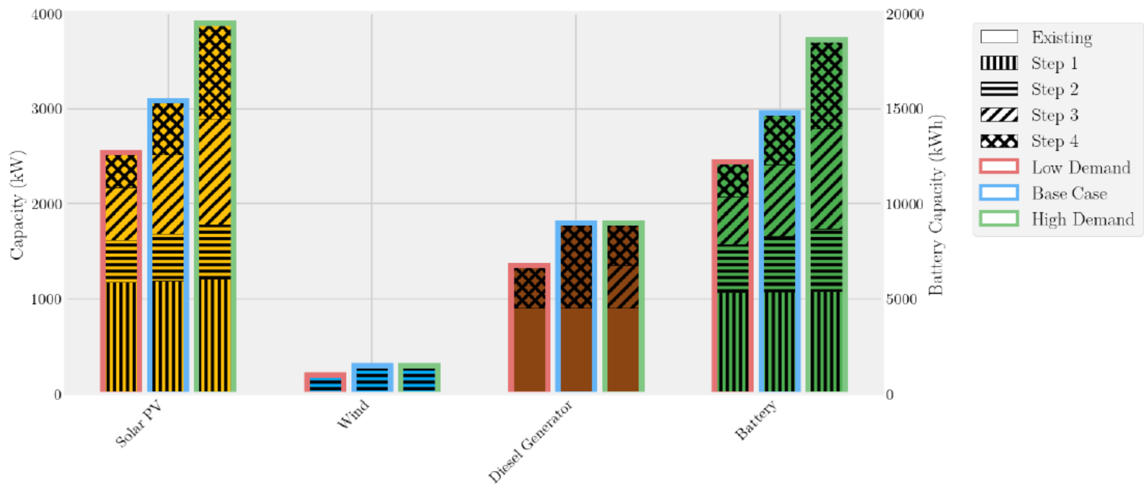

Figure 4 – Demand Sensitivity Results Plot

F. RESULTS – TECHNOLOGY COST SENSITIVITY

In this subsection, we examine the impact of renewable technology costs and diesel fuel prices on the model's results.

In the RES Best Case scenario, the initial investment in RES is lower compared to the other scenarios. Although the technology costs start at the same level for all cases, they decrease more rapidly in the RES Best Case, encouraging larger investments over time. The overall capacities for batteries and solar PV in the RES Best Case and the Base Case are quite similar. However, wind energy capacity is higher in the RES Best Case, reducing diesel generator usage during periods when solar PV production is low, and battery reserves are depleted.

This effect is particularly noticeable when analyzing the energy source distribution over time (see Table 7). In the final investment step, the RES Best Case is the least dependent on diesel generator production, although in the initial two steps, diesel reliance is slightly higher due to delayed investments in RES. Table 7 illustrates this trend, showing how wind energy substitutes diesel-

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generated power in the RES Best Case scenario, especially during morning hours when the battery is depleted.

Conversely, the RES Worst Case scenario reflects minimal reductions in renewable technology costs, resulting in smaller capacities for batteries and solar PV. However, wind energy capacity is higher compared to the Base Case scenario. This can be explained by the fact that wind technology prices, despite a lower overall reduction, continue to decrease relatively more than those for solar PV and batteries compared to the other scenarios. Therefore, wind installations become more attractive in the RES Worst Case scenario. Wind energy not only replaces solar PV but also offsets part of the battery storage requirement due to its more consistent generation throughout the day.

Throughout the project duration, reliance on diesel generators remains higher in the RES Worst Case compared to the Base Case (Table 7). The smaller learning rate for RES in this scenario is amplified by lower diesel prices, leading to a more sustained use of diesel generators for energy production.

For all three scenarios, the diesel generator capacity is consistently maintained at 900 kW throughout the project. Due to the 20-year operational lifespan of the existing generators, both units are fully replaced during the final investment step when their lifetimes are concluded.

Table 7 – Technology Cost Sensitivity Results

Technology	Scenario	Existing	Step 1	Step 2	Step 3	Step 4	Total
Solar PV (kW)	RES Best Case	0	1156	389	783	772	3100
	Base Case	0	1185	497	830	569	3081
	RES Worst Case	0	1227	317	626	573	2743
Wind (kW)	RES Best Case	0	0	400	100	0	500
	Base Case	0	0	300	0	0	300
	RES Worst Case	0	0	400	0	0	400
Diesel Generator (kW)	RES Best Case	900	0	0	0	900	1800
	Base Case	900	0	0	0	900	1800
	RES Worst Case	900	0	0	0	900	1800
Battery (kWh)	RES Best Case	0	5167	2495	3724	3413	14799
	Base Case	0	5355	2946	3747	2738	14786
	RES Worst Case	0	5618	1468	3635	2280	13001

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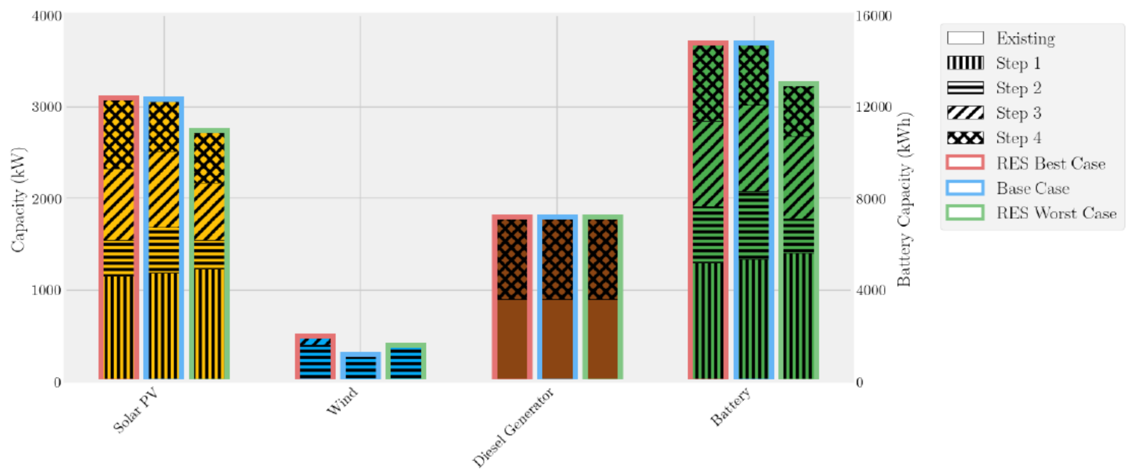

Figure 5 - Technology Cost Sensitivity Results Plots

G. RESULTS – ARCHITECTURE SENSITIVITY

This section examines the influence of system architecture on model outcomes by comparing two configurations: a DC Subsystem Architecture, where solar PV and batteries share a common inverter, and a No DC Subsystem Architecture, where solar PV operates through its own dedicated inverter, separate from the battery. The comparison focuses on the impact of architectural setup on system sizing, energy distribution, and overall cost-efficiency.

The results demonstrate that significant differences in system sizing are primarily observed in battery storage, while variations in solar PV sizing are minimal and largely negligible. Across all scenarios—RES Best Case, Base Case, and RES Worst Case—the total installed solar PV capacity remains relatively consistent between the two architectures. Conversely, Battery Storage reveals notable variances. The No DC Subsystem Architecture consistently results in smaller battery capacities, with reductions of approximately 2.3% in the RES Best Case, 2.5% in the Base Case, and 4.4% in the RES Worst Case. These reductions arise from the less efficient energy transfer process between solar PV and the battery in the No DC Subsystem Architecture scenario. As charging the battery with solar PV in a No DC Subsystem Architecture requires additional conversions from DC to AC and then back to DC for storage, it incurs higher losses. Consequently, battery storage becomes less economically viable in the No DC Subsystem Architecture scenario, leading to a preference for smaller battery capacity.

This diminished battery capacity directly results in increased reliance on the Diesel Generator (Table 8). In the DC Subsystem Architecture setup, the larger battery is better equipped to manage peak loads and energy fluctuations, thereby reducing the necessity for generator usage.

The sizing of Wind Turbines remains unchanged between the two configurations, indicating that wind integration is not directly impacted by the inverter arrangement. This consistency persists despite solar PV becoming less attractive in the No DC Subsystem Architecture due to elevated conversion losses when charging the battery.

The Levelized Cost of Energy (LCOE) underscores the economic trade-offs between the two architectures. In the RES Best Case, the DC Subsystem Architecture setup achieves a lower LCOE of 18.35 cents/kWh compared to 18.66 cents/kWh in the No DC Subsystem Architecture, representing a 1.7% improvement. This cost advantage is maintained across other scenarios, with the Base Case

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showing a 1.7% reduction (19.25 vs. 19.58 cents/kWh) and the RES Worst Case reflecting a 1.4% decrease (19.96 vs. 20.25 cents/kWh). These disparities highlight the efficiency of the DC Subsystem Architecture in minimizing energy losses and optimizing battery utilization.

Table 8 – Grid Architecture Sensitivity Results

Technology	Scenario	Existing	Step 1	Step 2	Step 3	Step 4	Total
Solar PV (kW)	RES Best Case	0	1171	387	834	761	3153
Solar PV (kW)	Base Case	0	1198	490	821	579	3088
Solar PV (kW)	RES Worst Case	0	1244	228	670	551	2693
Wind (kW)	RES Best Case	0	0	400	100	0	500
Wind (kW)	Base Case	0	0	300	0	0	300
Wind (kW)	RES Worst Case	0	0	400	0	0	400
Diesel Generator (kW)	RES Best Case	900	0	0	0	900	1800
Diesel Generator (kW)	Base Case	900	0	0	0	900	1800
Diesel Generator (kW)	RES Worst Case	900	0	0	0	900	1800
Battery (kWh)	RES Best Case	0	5091	2403	3902	3063	14459
Battery (kWh)	Base Case	0	5261	2705	3778	2672	14416
Battery (kWh)	RES Worst Case	0	5556	1235	3222	2421	12434

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