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ENERGY ACCESS AND GREEN TRANSITION COLLABORATIVELY DEMONSTRATED IN URBAN AND RURAL AREAS IN AFRICA

D2.4

Energy Flow Patterns for Productive Uses of Energy

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DEM	Demonstrator, pilot, prototype, plan designs	
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OTHER	Software, technical diagrams, etc.	

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I. PROJECT SUMMARY

The ENERGICA project is an ambitious collaboration between 11 African-based partners and 17 European organizations with offices or subsidiaries in Africa, which is aimed at promoting energy access and sustainable energy development. The project's primary objective is to demonstrate the efficient implementation of Renewable Energy Technologies (RETs) that are tailored to the specific needs of local contexts. This will be achieved through the deployment of three demonstration sites, which will be managed by local Energy Transition Boards, and will utilize community-scale Integrated Community Energy Systems (ICESs).

The project's focus on innovative technologies and methodologies is expected to yield positive social, environmental, technical, and economic impacts, resulting from the high energy efficiency and low carbon emission RETs. One specific initiative of the project is the development of innovative nano grids in the rural Diana region of Madagascar. To ensure the project's replication and sustainability, the energy flow patterns and associated value flows within local communities are predicted as outlined in this report.

II. OBJECTIVE AND EXECUTIVE SUMMARY

The ENERGICA project aims to promote energy access and sustainable energy development through collaboration between partners in Europe and Africa. One of the project's focuses is developing innovative solutions for productive use systems in rural Madagascar through nano-grids.

The project aims to achieve a strong market uptake and replication with local environmental and socio-economic benefits and to support local market uptake through innovative business models and capacity-building activities. The project also aims to contribute to fighting climate change and improving health and social conditions for up to 1500 local stakeholders across Africa.

The overall aim of deliverable D2.4 is to provide insights into the impact of the productive uses integration on a community level and to describe the significance of productive uses for the evolution of energy access in the demonstrator region in Madagascar. Within this global picture, the investigation aims to analyse the bilateral relation between community structure and Productive Uses of Energy (PUE) integration nano grids. This research objective may be broken down into two sub-objectives, which are a). to understand how socio-economic characteristics influence residential electricity consumption and b). to understand how the residential electricity consumption patterns interact with the electricity consumption patterns of PUEs. Combining the results of both unlocks insights to consider during community energy system planning and PUEs integration in communities. The investigation is based on a case study to enable an in-depth analysis. The findings are subsequently embedded into qualitative observations to derive generalized learnings.

This report emphasizes the importance of engaging with local stakeholders and promoting participatory decision-making processes when designing community-level energy systems that are inclusive, sustainable, and effective. It also highlights the need for further research and experimentation to fully understand the dynamics of integrating PUEs into community-level energy systems in different contexts, explore other PUE options, and identify innovative solutions that are better suited to specific settings.

More information on the project can be found at https://www.energica-h2020.eu/

III. CONTENT

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VI. ACRONYMS

CSO	:	Civil Society Organisations
CSM	:	Community Structure Mapping
DC	:	Direct Current
ENERGICA	:	ENERGy access and green transition collaboratively demonstrated in urban and rural in AfrICA.
EU	:	European Union
HH	:	Household
HUD	:	Hudara
ICES	:	Integrated Community Energy Systems
JIRAMA	:	Jiro Sy Rano Malagasy
kWh	:	Kilo Watt per Hour
LCOS	:	Levelised Costs of Systems
LCOE	:	Levelised Cost of Electricity
LED	:	Light Emitting Diode
LVC	:	Local Value Chain
MFIs	:	Micro-Finance Institutes
Oemof	:	Open Energy Modelling Framework
PUE	:	Productive Uses of Energy
RE	:	Renewable Energy
RETs	:	Renewable Energy Technologies
SACREEE	:	SADC Centre for Renewable Energy & Energy Efficiency
SMEs	:	Small and Medium-Sized Enterprises
TAC	:	Total Annualised Costs

1. INTRODUCTION

Madagascar is the fourth largest island in the world, with a geographical area of 587,295 km2 and a population of 25,674,196 inhabitants according to the 2018 general population census. It has twenty-two regions of administrative divisions with Antananarivo as the capital city.

According to SADC Centre for Renewable Energy & Energy Efficiency (SACREEE), Madagascar has one of the lowest electrification rates in the Southern Africa Region: 17% on average with many disparities (more than 30% in urban areas and less than 5% in rural areas) with massive potential to generate 7,800 MW of electricity from hydropower and the average solar energy potential is estimated at 2,000 kW/m^2 per year, with potential for wind energy across many regions. About 50% of the electricity is generated from imported fuel oil and coal whereas the other half is produced via national hydro projects [26].

The majority of the island's energy presently comes from diesel and heavy fuel, with residential customers being the main consumers. Although the primary energy supply is largely obtained domestically, the nation depends on imported fossil fuels for its needs. SACREEE reports indicate that accessibility to generation sites is hindered by infrastructure limitations, leading to frequent power outages. In 2015, the national power utility, Jiro Sy Rano Malagasy (JIRAMA), recorded an estimated 799 instances of load shedding [26].

Madagascar's Energy Policy in 2015 aimed to accelerate the rate of electrification by utilizing renewable energy sources to ensure 260,000 households (HH) are connected annually. JIRAMA, a vertically integrated state-owned energy and water company, oversees the majority of the transmission and distribution assets in the country according to SACREEE. However, there is a growing presence of Independent Power Producers (IPPs) who now contribute up to 30% of the overall generation capacity as of 2014 [26].

Access to reliable and affordable energy is a crucial factor for sustainable development, particularly in rural areas of developing countries. In recent years, there has been growing interest in the integration of PUEs into community-level energy systems to enhance energy access and promote economic activities. However, there is still limited understanding of how PUEs can be effectively integrated into existing energy systems and how they can impact community dynamics and socio-economic development.

The national census of 2018 indicated that the Diana Region covers an area of 19,266 km^2, with a population of 889,736 and is more agriculturally productive with higher production of rice, cocoa, sugarcane, Vanilla, cashew nuts, shrimp, and other farm produce. However, more of the produce goes to waste due to poor post-harvest handling systems. For example, the rice hauling machines currently in use are diesel-powered, which is expensive to run and maintain. They also cause health complications from inhaled fumes. Cooling facilities are also a challenge. The current few nano grid solutions have not exhibited any negative impact on the flora and fauna. Placing solar-powered plants on communal land or individual households has proven not to generate any land ownership conflicts or tensions. The absence of a formal local development strategy or energy community structure has caused sustainability challenges to some solar-powered projects [1].

To address this gap, this report presents a case study analysis of the bilateral relationship between community structure and PUE integration in nano grids in Madagascar. Specifically, to understand how socioeconomic characteristics influence how residential electricity consumption patterns interact with PUEs consumption patterns, and what insights can be gained from combining these results for community energy system planning and PUE integration. The analysis is based on a combination of quantitative and qualitative data collected through household surveys, focus group discussions, and expert interviews. The results are generalized, and predictive interpretations are conducted to provide insights into the potential impacts of PUE integration on community-level energy access and on a larger scale.

The study highlights the potential for scale up of PUE integration to enhance the viability and impact of decentralized renewable energy solutions but also emphasizes the need for careful planning and monitoring to ensure social and environmental sustainability. The report emphasizes the importance of participatory approaches to community energy planning and decision-making to ensure that PUE integration is socially acceptable and sustainable over the long term.

2. STATUS QUO

Understanding how socio-economic characteristics impact residential electricity consumption and how it interacts with productive use of energy (PUE) consumption patterns can provide valuable insights into designing effective and sustainable community-level energy systems. This information can be used to design targeted interventions to reduce energy demand and increase system efficiency, while also identifying potential conflicts or synergies between residential and productive users. Additionally, combining these insights can help identify opportunities for income generation through PUE activities, which can offset household energy costs. Engaging with local stakeholders and promoting participatory decision-making processes is crucial in designing community-level energy systems that integrate both residential and productive uses. Ultimately, designing effective and sustainable community-level energy systems can promote economic growth and inequalities reduction in rural areas. Hence understanding the structure of the community, the status of energy access and the productive use of energy can guide in predicting the future of energy access and productive uses when energy access is improved.

2.1. Community Structure

Community structure refers to the various ways in which individuals or groups within a community are organized and interact with each other and are brought together by choice or force of circumstance, and who have learned to live, work, and play together [2]. It encompasses the social organization, relationships, and networks that exist within a community, as well as the distribution of resources and power among its members [3]. Community structure can be formal or informal and can be influenced by factors such as cultural traditions, economic conditions, political systems, and historical events. Examples of community structures include families, neighbourhoods, religious organizations, schools, and businesses. Understanding the community structure is important for effective community development, planning, and decision-making processes. This can be achieved through Community Structure Mapping (CSM), a method used in social network analysis to identify and analyse the patterns of relationships between individuals or groups within a community or organization [3]. It involves mapping out the social connections and interactions between members of the community or organization and analysing the structure of the network to identify clusters or sub-groups of individuals who are closely connected. Community Structure Mapping can provide valuable insights into the social dynamics and power structures within a community or organization and can be used to inform strategies for community development, organizational change, or social interventions [4]. In this case, the community structure will be instrumental in understanding the PUE and predicting the roles the communities can play in the implementation, utilisation, and sustenance of the PUE projects.

According to the ENERGICA's baseline study findings, the structure of the community in Madagascar is diverse, with different ethnic groups and a common language, Malagasy spoken across the country. French is also used in official settings. Most of the people, according to the survey, identify themselves as farmers (44%), followed by fishermen (16%), and traders (14%). The household structure of the community is comprised of an average household size of 5 adults and 1 child. Most households were headed by men (70%), and the average age of household heads was 47 years old. The social fabric underscores the importance of culture, family, and community. These values should be considered when designing and implementing projects related to energy access and green transition. Community engagement and participation are critical components for ensuring the success and sustainability of such projects.

Additionally, most households rely on traditional biomass fuels such as wood and charcoal for cooking and heating. However, 48.2% of people in the Diana region have access to electricity through Solar Home Systems either directly in their households or through their Neighbours as was indicated in the ENERGICA's baseline survey.

Nevertheless, the results obtained from the baseline survey revealed notable obstacles, including limited educational attainment and a prevailing culture of pursuing "quick money" during the harvesting season, particularly in the context of vanilla harvesting. This cultural inclination toward immediate financial gain can lead to the adoption of unsustainable practices, posing significant risks to both the environment and ongoing endeavours aimed at promoting economic development. It becomes evident that addressing these practices is crucial to safeguard long-term environmental preservation and foster sustainable economic progress.

Addressing inequalities, improving access to basic amenities, promoting economic development, and addressing infrastructure challenges are critical components for improving the social fabric of these communities. It should be noted that these characteristics may not represent the entire population of Madagascar and may vary across different regions and ethnic groups.

As PUE can refer to a variety of activities that utilize energy to generate income or improve productivity, such as rice milling, food processing, water pumping, and targeted use of energy to address the economic needs of a social group will be necessary. In the case of the Diana region, farming and small-scale trading were the most common economic activities. The communities rely on rice farming and fishing as the major farming activities and vanilla farming follows closely. For the case of rice hauling and freezing services, the identified community structure from the baseline assessment survey included community leaders (including traditional and religious leaders), local organizations, women's groups, entrepreneurs, youth groups, fisher groups, private sector organizations, and energy providers. These groups will be instrumental in the support of the implementation, utilisation, and sustainability of the PUEs.

Community leaders can contribute to the PUEs value chain in several ways. One key role is to raise awareness among community members about the benefits of PUE, including the potential to boost economic development and improve quality of life. They can also serve as a liaison between the community and PUE stakeholders, facilitating mobilisation, communication, and collaboration. They also can have influence over decision-making processes and resource allocation. By advocating for the integration of PUE initiatives into local development plans, they can help ensure that these programs receive the necessary support and resources to succeed. As they are already viewed highly by the societies they represent, they can be as well role models and advocate for the importance of sustainability and environmental stewardship. By promoting the use of clean and renewable energy sources, they can help ensure that future generations can continue to benefit from the resources and opportunities available in their communities. Community leaders will be instrumental during conflicts. They can help to resolve conflicts that may arise between different stakeholders involved in PUE activities, services and products and ensure that the interests of their communities are considered.

Civil society groups can play a critical role in promoting the development of PUE by engaging with and empowering local communities through awareness raising on the benefits of PUEs, and training on business and entrepreneurial skills, which in turn will promote the uptake of the technologies by the local communities. They can also enhance advocating for supportive policies including policies related to access to finance, market access and energy infrastructure development, and building partnerships to drive sustainable change. Additionally, they can support the monitoring and evaluation of the PUEs through impact assessment and identify areas for improvement. Lastly, they will be instrumental in fostering participation and partnerships building between the different stakeholders in the PUE value chain including communities, entrepreneurs, energy providers, financial institutions, government regulatory agencies, policymakers and consumers of the value added produced by the communities' economic activities.

Women's groups can play important roles in various stages of the PUE value chain. They can become entrepreneurs and start their own PUE-related businesses, such as providing laundry services, salon businesses and hotels by using clean energy and utilisation of clean energy appliances. The groups can offer a great quorum for learning and training other members of the community on PUE technologies, such as solar panel installation or making and usage of efficient cookstoves. Women can participate in decision-making processes related to the planning, implementation, and monitoring of PUE initiatives. This includes being involved in community consultations and contributing to the design of PUE projects. They can provide feedback on the effectiveness of PUE interventions and suggest ways to improve them. This feedback can help ensure that PUE initiatives are responsive to the needs and priorities of women in the community and implementation of the responsive energy and gender approaches. They can also raise awareness about the benefits of PUE, such as reducing energy inequalities and improving health outcomes contributing to women's empowerment and gender equality.

Entrepreneurs can play a significant role in the PUE value chain by identifying new market opportunities and developing innovative solutions that leverage PUE. They can create new businesses that provide energy-efficient products and services, such as energy-efficient appliances, solar-powered irrigation systems, and cooking stoves. Entrepreneurs can also help to facilitate access to finance and other resources that are needed to scale up PUE activities, and they can work with local communities and organizations to identify and address specific energy needs and challenges. Additionally, entrepreneurs can contribute to capacity-building efforts by providing training and mentorship programs that help to develop new skills and capabilities within local communities.

Youth groups can play various roles in the PUE value chain, such as identifying and promoting opportunities for income-generating activities that leverage PUE, conducting awareness campaigns to educate communities on the benefits of PUE, providing training and skills development for youth in PUE-related fields, and collaborating with other stakeholders in the PUE ecosystem to facilitate access to financing and technical assistance for PUE projects. Additionally, they can serve as important catalysts for innovation and creativity, bringing fresh perspectives and ideas to the table and driving the development of new PUE solutions that meet the evolving needs of their communities.

Fishermen can play several roles in the PUE value chain, such as using solar-powered boats to transport goods and people to and from fishing areas, installing solar panels on boats to power fishing equipment and refrigeration systems, using solar-powered ice makers to preserve their catch, and using energy-efficient stoves for cooking and smoking fish. Additionally, fishermen can also form cooperatives to jointly purchase and maintain energy equipment, access credit for investing in energy technologies, and negotiate fair prices for their products. By adopting these energy-efficient practices and technologies, fishermen can reduce their costs, increase their productivity, and improve the quality of their products.

Private sector organizations can play a significant role in the PUE value chain by providing financial, technical, and operational support. They can invest in PUE projects, provide financing, and credit facilities, and offer technical expertise in areas of need as will be identified by the communities. Private sector organizations can also offer marketing and distribution support, supply chain management expertise, and access to markets for PUE products, and services. Furthermore, private sector organizations can also support PUE through corporate social responsibility programs, partnerships, and collaborations with local communities and other stakeholders.

Finally, energy providers will provide reliable, accessible, and affordable energy services that enable the development of productive uses of energy. This can be done through the installation of energy infrastructure such as nano grids, mini-grids, solar home systems, and other RETs. Energy providers can also offer financing solutions for PUE projects and provide technical assistance to ensure the successful implementation of these projects. In addition, energy providers can partner with local organizations to raise awareness about the benefits of PUE and to identify opportunities for PUE projects that can benefit the community. Other services they can be keen to provide are the installation, maintenance, distribution, and disposal of the PUE infrastructure.

2.2. Access to Energy

A more equitable and sustainable economy is primarily driven by access to energy [5]. More than two-thirds of Malagasies in the Diana region do not have access to clean energy in their households. Those who have access are mainly connected to nano grids and other sources like petrol, and diesel. Solar Home Systems were the most common RE source mainly used for lighting and communication with other energy servings like cooking and productive use not utilized. The mean monthly HH income is $58.81 with 16% dedicated to energy consumption [24]. There is a wide knowledge of RE and the impact of climate change amongst the community members in general. However, most of the Malagasies acknowledged the challenges of climate change but more so indicated its impact on them being food security challenges, water shortage and increased cost of fuel fossil fuel, and wood. They also attributed the high cost of acquiring RE on climate change. Despite the energy access challenges the people of Diana region face, like, limited services, energy subscription fees, battery size and lifespan for those using solar-powered batteries, and cost of diesel, petrol and firewood/charcoal, and the impact climate change had already had on them, they expressed willingness to support RE projects in the locality. The major benefits RE projects can have to the people will be environmental benefits, more reliable power, increased local employment, reduce social and economic gap, and promote community engagement [24].

Access to cooling and freezing services is poor, according the ENERGICA's baseline survey, only 31.2% of the people had access. Respondents are, however, willing to pay to access the services both from their households and their neighbourhood, with the most common use being to make ice blocks, cool beverages, and conserve meat and fish. The largest amount respondents are willing to pay to access cooling and freezing services is $94.61. Cost was not found to be a factor that would be a factor to considered when people made decisions on their choice of service providers for cooling and freezing services, as the differences in the monthly costs between service providers were not statistically significant.

The baseline survey reported a maximum mean expenditure of $118.26 per month for access to agricultural machines for those who did. Cost is a factor considered when people are making decisions on their choice of service providers and locations for access to stationary agricultural machines. The differences in the monthly costs of using stationary agricultural machines were statistically significant (p value <0.05) between various locations, with respondents spending the most when the machines were in their neighbourhoods, less than one hundred meters from their households.

2.3. Productive Uses of Energy

Productive Use of Energy, or PUE, refers to the use of electricity-powered solutions that support economic activity and provide users with more income than their previous solution [25]. Renewable energy sources are often used because they are cheaper or the only available option.

Decentralized renewable energy solutions such as nano grids have emerged as a promising approach to enhance energy access and promote economic activities in rural areas of Madagascar. Nano grids are small-scale electricity distribution systems that serve a limited number of households and businesses within a community.

PUE is a promising approach to enhance energy access and promote economic activities in rural areas of countries in the global south, particularly through decentralized renewable energy solutions such as nano grids. PUEs are seen as a key component of nano grids, as they can provide additional revenue streams and reduce dependence on external markets for goods and services. However, there is still limited understanding of how PUEs can be effectively integrated into existing energy systems and how they can impact community dynamics and socio-economic development. The case study analysis presented provides insights into the impact that PUE integration has on community-level energy access and describes the significance of productive uses for the evolution of energy access in Madagascar. The analysis shows that socio-economic characteristics influence residential electricity consumption patterns in nano grids and that residential electricity consumption patterns interact with PUE consumption patterns. Overall, while there is still much to learn about how best to integrate PUEs into community-level energy systems, the case study analysis provides valuable insights into their potential benefits and challenges. By continuing to explore innovative approaches to PUE integration and promoting sustainable development through renewable energy solutions, working towards achieving universal access to affordable, reliable, sustainable, and modern energy for all will be possible.

PUEs can have a significant impact on inequalities reduction and gender empowerment by creating new income-generating opportunities for women and other marginalized groups as highlighted in D2.1 of ENERGICA. However, they also present a possibility for divergent consequences. One potential outcome could be the consolidation of power among affluent males within the community, which, in turn, may perpetuate gender roles and contribute to an increase in gender-based violence. This speculation highlights the potential interplay between social dynamics and power structures, shedding light on the complex ramifications of such a scenario.

The success of PUE integration depends on a range of factors, including the availability and affordability of energy technologies, the local market demand for PUEs, the capacity of local institutions to support PUE development, and the social acceptance and participation of community members. The case study analysis highlights some of the possible challenges associated with PUE integration, such as limited access to finance, inadequate technical skills and knowledge among community members, and potential conflicts between residential and productive electricity uses. To address these challenges, innovative financing mechanisms such as pay-as-you-go models or microfinance schemes can be used to increase access to capital for PUE development. Capacity-building programs can also be implemented to enhance technical skills and knowledge among community members.

Socioeconomic characteristics that could influence the residential electricity consumption in nano grids are:

1. Household income: households with higher incomes tend to consume more electricity than those with lower incomes, as they can afford to purchase more appliances and use them more frequently.
2. Household size: larger households tend to consume more electricity than smaller households, as they have more people using appliances and lighting.
3. Education level: households with higher levels of education tend to consume more electricity than those with lower levels of education, as they are more likely to own and use appliances such as computers and televisions.
4. Economic activities: households with occupations that require the use of electricity, such as small business owners or artisans, tend to consume more electricity than those with occupations that do not require electricity.
5. Age: younger households tend to consume more electricity than older households, as they are more likely to own and use modern appliances and electronics.

It is important to note that these socio-economic characteristics are not deterministic factors and may interact in complex ways with other factors such as cultural norms, access to finance, or availability of energy-efficient technologies. Therefore, a comprehensive understanding of residential electricity consumption patterns in nano grids requires a combination of quantitative and qualitative data collection methods, which were implemented in ENERGICA's baseline assessment and used as supplementary data for this report.

The interaction between residential electricity consumption patterns and PUE consumption patterns in nano grids can be complex. In general, PUEs are typically designed to operate during specific times of day or week, depending on the type of activity they support (e.g., milling, welding, or refrigeration). This means that PUE consumption patterns may not align with residential consumption patterns, which tend to be more evenly distributed during daytime. They also tend to consume more electricity overall than households without PUEs, due to the additional energy required to power productive activities. However, this additional consumption is often offset by increased income generation from PUE activities. Conflicts between residential and productive electricity use can arise when there is limited capacity within the nano grid system to meet both types of demand simultaneously. This can lead to voltage fluctuations or power outages that can disrupt both residential and productive activities.

To address these challenges, a range of strategies such as load management techniques (e.g., scheduling PUE activities during off-peak hours), energy storage solutions (e.g., batteries or flywheels), or grid expansion to increase capacity and ensure reliable electricity supply for both residential and productive uses could be applied.

3. CASE STUDY

3.1. Approach and Outline

The overall approach to address the research objectives follows the methodological flow illustrated in Figure 1. A case study was selected to allow for an in-depth analysis of the impact of PUE for the community. The selected case study, the village of Ambohimena, lies within the demonstrator region in Madagascar and can be assumed to be representative of rural settings in the demonstrator region. The comprehensive insights from the case-study analysis are utilized in the last part of this deliverable (3) to derive generalized statements about the significance of PUE integration for communities in the demonstrator region of Madagascar.

As is depicted in Figure 1 the case study is structured into three parts (2.1.3) Consumption data analysis, (2.4) Scenario modelling, and (2.5) Modelling results.

For the first part of the case study analysis, a data set was made available by Nanoé, which contains both descriptive socio-economic data and historical consumption data for a large number of energy system users in Ambohimena. This set of data is an essential addition to the information based described in the first part of this deliverable (1) the outputs from the previous project deliverable, as the consumption data and socio-economic data are available for the same users and thus it allows for an analysis of correlations. The data analyses conducted resulted in two primary outputs, namely the identification of socio-economic consumption determinants and the definition of consumption scenarios. The identified determinants describe the relationship between socioeconomic characteristics and energy consumption, enable more informed system designs and support considerations regarding energy consumption pathways. The findings will be used in subsequent tasks of the project for the planning and development of tools in Work Package 4. The second output of the initial step of the case study analysis is designated representative consumption scenarios. The representative consumption scenarios serve as a basis for the modelling and cover a range of typical and critical consumption scenarios (2.3).

The second part of the case study analysis consists of the development of models to study the integration of productive uses in the energy system. The model development is a multi-stage process starting with the selection of the specific productive uses to be investigated in the case study. The selection of productive uses is followed by the identification of applicable integration scenarios, which were derived from a series of interviews conducted during a field trip to the demonstrator location. For each of the identified integration scenarios one energy system model was developed based on the elementary energy system models developed in Task 1.2.3. The models provide technical, economic, and operational evaluation criteria.

The final part of the case study analysis combined the output of the first part, the designated consumption scenarios, with the output of the second part, the set of energy system models. For each of the selected productive uses, all identified PUE-integration scenario models are run using the input from all specified consumption scenarios, successively. This resulted in many scenarios considered reflecting both the diversity in terms of consumption behaviour and the diversity in potential integration options. The modelling results enable a multi-layered and extensive evaluation, an overview of which is provided in the following.

First, the conducted modelling exercise allows for the evaluation of the different PUE-integration scenarios under the assumption of different consumption behaviours. This provides insights into the respective preconditions that need to be met for a successful integration and in conclusion, enables predictive statements regarding the potential impacts on the communities utilizing the energy systems. As the consumption scenarios include a representation of different pathways in socio-economic development, the modelling results allow for an evaluation of long-term impacts on the community. To fully understand the consequences for the community, the modelling results are put in the context of the respective community structure and the respective operational environment, by including learnings from the conducted interviews.

Second, the different integration scenarios can be evaluated and compared, from a technical, economic, and operational point of view. The comparison of different integration scenarios enables both the selection of suitable integration approaches and the evaluation of the scope of potential PUE-integration outcomes. This provides insights into the risks associated with the integration of PUE. To derive operational and development recommendations is of essential importance to include a discussion on how close the depicted scenarios are to the reality of integrating the PUE.

Third, in addition to the comparison of different integration approaches for a series of potential consumption behaviours, the modelling results enable a comparison of the two PUE selected as part of this case study analysis (2.5)

The investigation conducted in the case study analysis is based on data from one village in the demonstrator region of the ENERGICA project. This deliverable contains an analysis beyond the scope of this case study. Learnings from the case study analysis are generalized and predictive interpretations are conducted to provide insights into the potential impacts of PUE integration on a larger scale (3). The interpretation beyond the scope of the case study is based on previous project outputs and the introductory section of this deliverable.

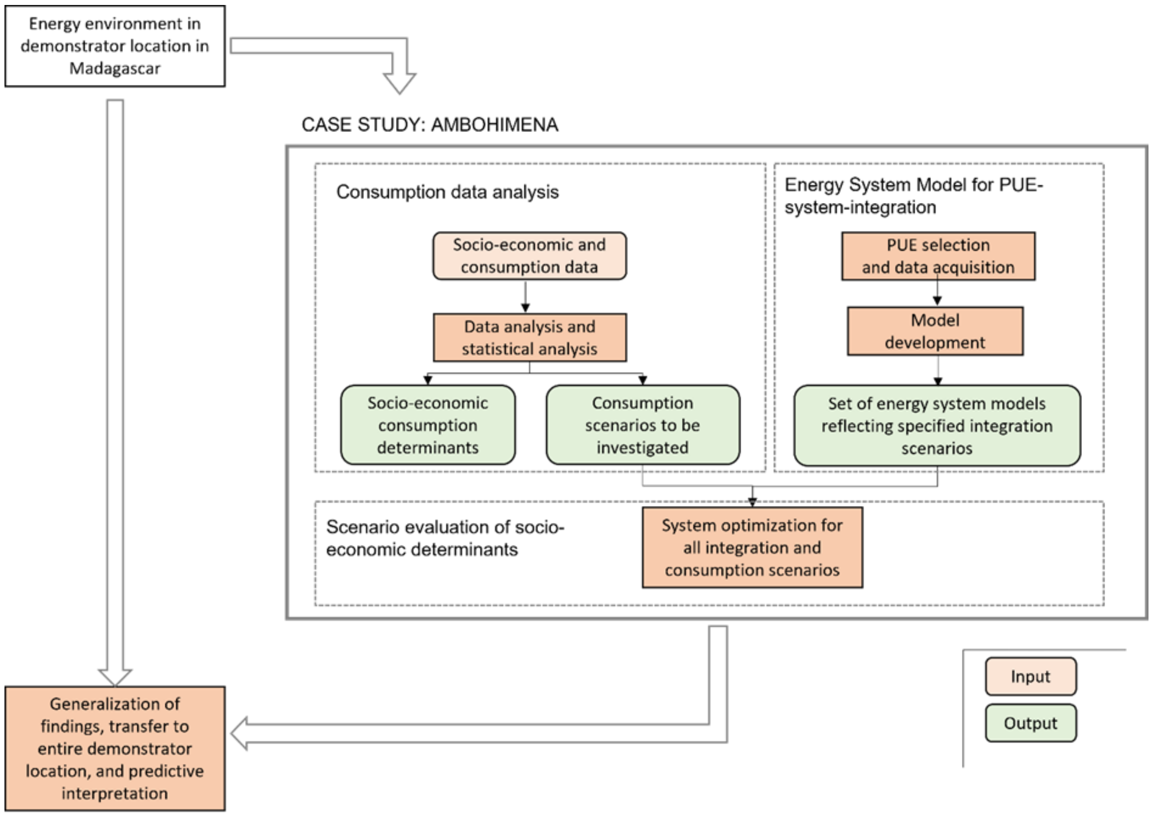
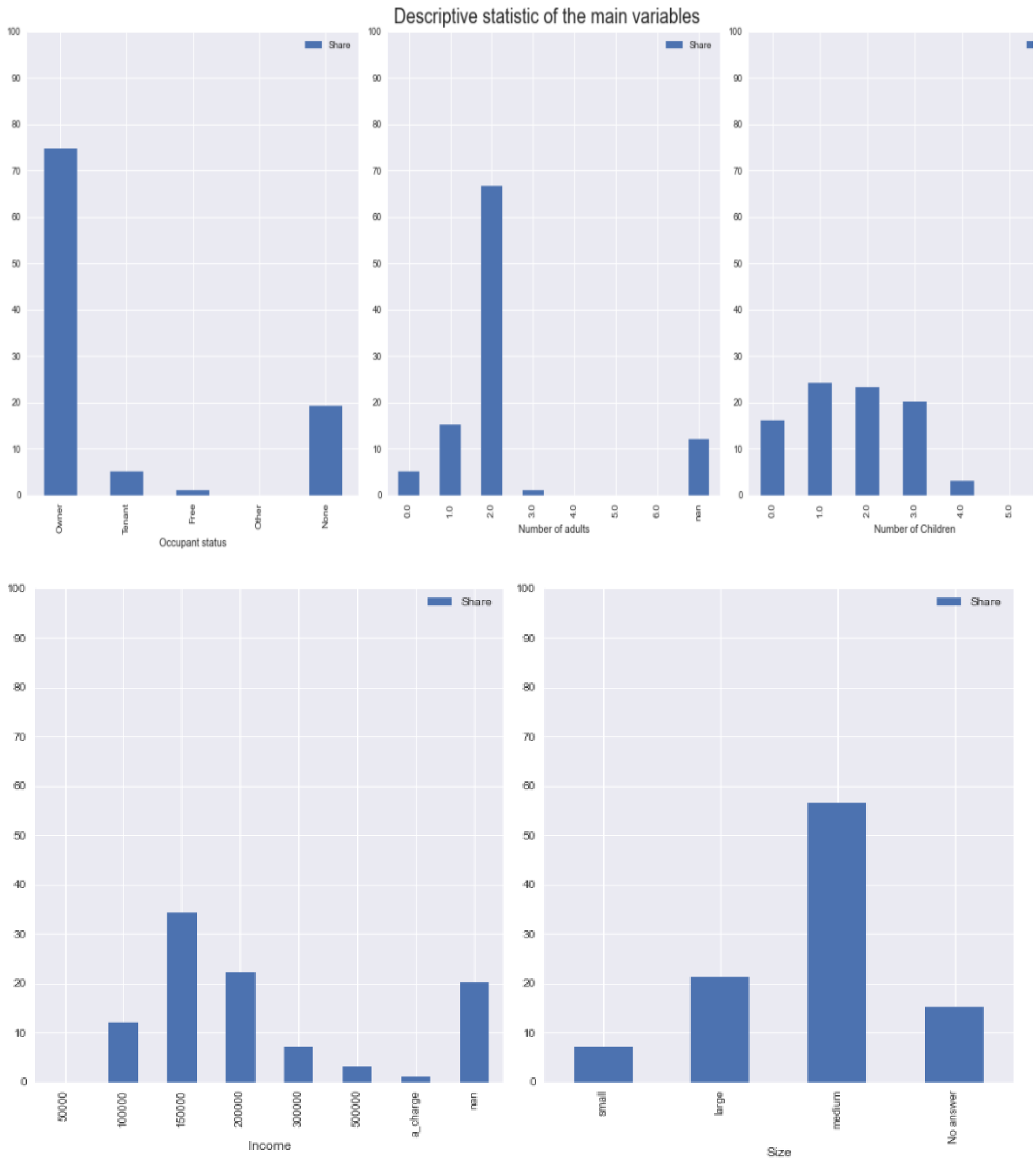


Figure 1: Methodological framework and workflow of the case study.

3.1.1. Case Study Description

The assessment is based on a case study located in the Ambanja district, which is in northern Madagascar. The key-informant interviews conducted with current owners of electrical and diesel-based PUE were conducted in various villages around the city of Ambanja. The advanced statistical analysis and energy system modelling was conducted based on data retrieved by the local partner Nanoé in the Ambohimena village. Ambohimena is a rural municipality in northern Madagascar. Ambohimena belongs to the Ambanja district, which is part of the Diana region. Ambohimena is located close to, but not in the Mangrove area. Most inhabitants live mainly from land cultivation, animal farming and fishing. The median monthly income of survey households is 150,000 Ariary (ca. 31€). The survey was conducted with 209 households and provides insights into the electricity access prior to the deployment of nanogrids. Before the deployment of the nano grids, 24% of the survey participants in Ambohimena owned electrical production devices. Most commonly, the survey participants owning production devices owned solar systems (55%), fuel generators (22%), and solar kits (12%). Others owned rechargeable batteries (8%) and solar lamps (4%). A follow-up survey in 2022 revealed that almost half (47%) of the survey participants, who had been contacted during the initial assessment had opted to get connected to a nongrid. Figure 2 illustrates selected descriptive statistics of a reduced number of households (n = 107), who in 2022 were connected to a nanogrid in Ambohimena. This data set will later be used in a subsequent part of the case study for the analysis.



a)

b)

Figure 2: Selected descriptive statistics of a representative share of inhabitants of Ambohimena village.

The main objective of the statistical analysis is to understand how and why the energy consumption patterns of individuals and a population may change. The information is useful when evaluating the integration of PUE in the energy system, as interactions of residential electricity consumption and the productive uses on the energy system level are obvious. Following the workflow drafted in Figure 1, the following section first describes the data used in our case study. Then, the electricity consumption data will be analysed to derive trends in the evolution of consumption caused by external factors. Subsequently, the socioeconomic data of individuals in the sample group will be combined with the electricity consumption behaviour to investigate the potential impact of socio-economic characteristics towards electricity consumption patterns.

3.1.2. Electricity Consumption Patterns

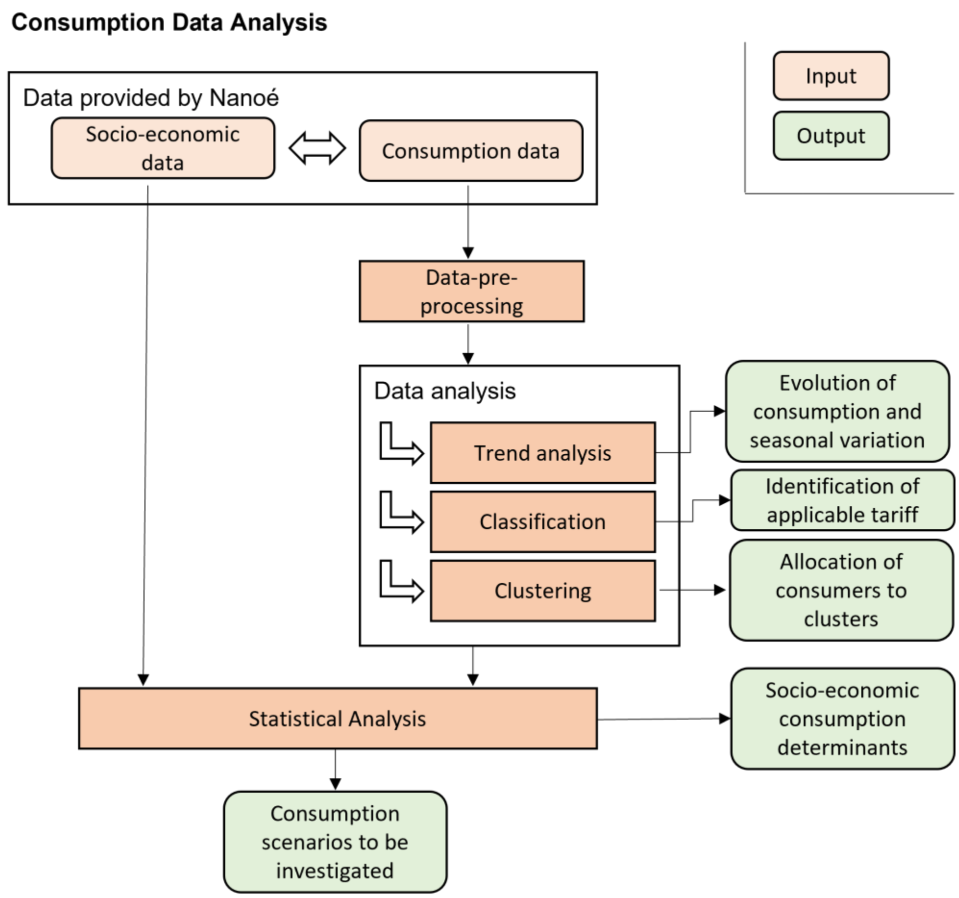


Figure 3: Workflow and outline of the second section.

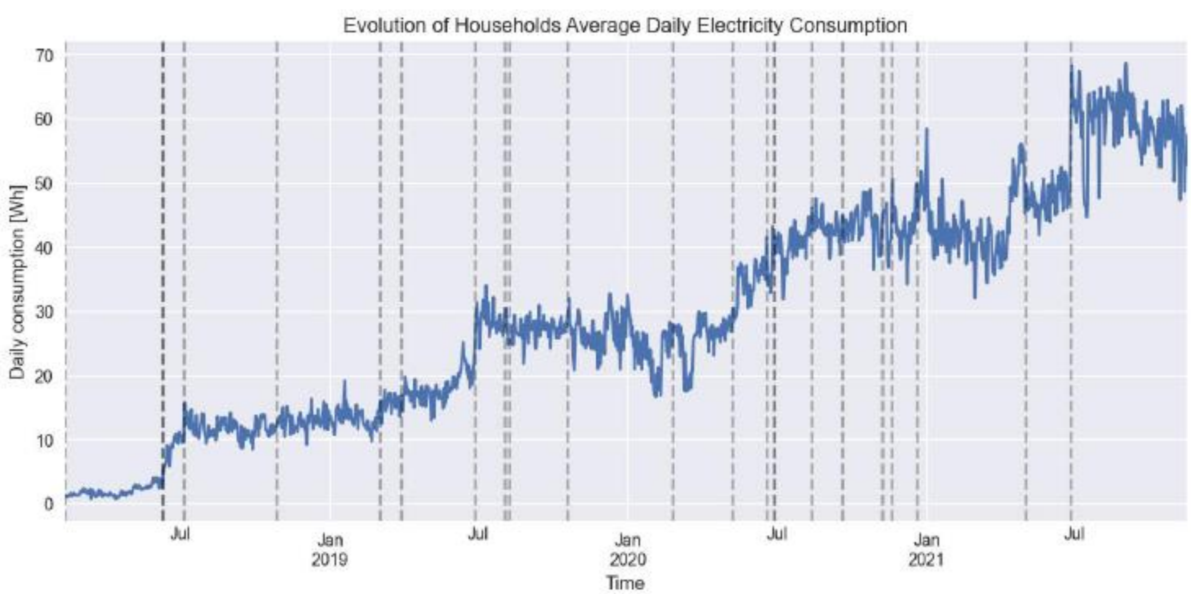
3.1.3. Consumption Data Analysis

Electricity consumption data was provided by Nanoé. The data shared included amongst other measurements of voltage (hourly resolution) and current (10 minutes resolution) of Nanoé clients in Ambohimena between January 2018 and December 2021. The data was cleaned to cover for eventual reboot events of the logging system or other missing values. Assuming a constant voltage, the power consumption was calculated and interpolated to receive electricity consumption data in hourly resolution to meet the requirements of the modelling framework applied (2.4). Clients without any information were removed manually. The remaining clients with consistent data information count n = 107. The manipulated data was saved in Excel files and passed to a Python-capable environment for further processing.

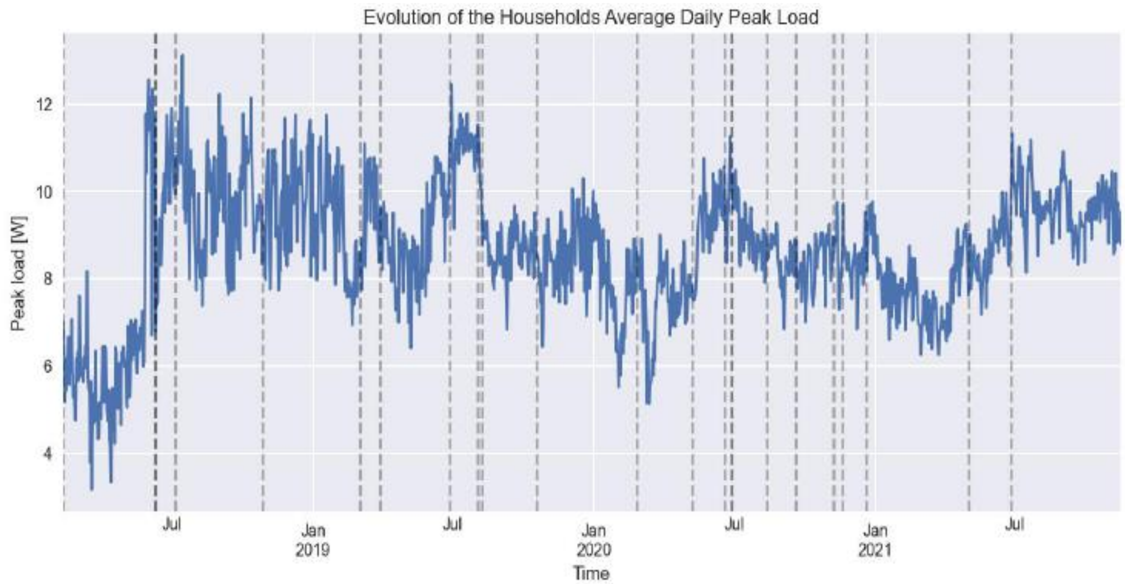
3.1.3.1. Trend Analysis

Aside from variations depending on the time of day, the electricity consumption of individuals and communities might change in various time scales, driven by external factors. Evidently, the electricity consumption may vary with the seasonality, depending on the activities of electricity users. Further, when improving electricity access, it may be assumed that increased activities evolve that require electricity, leading to an increase in the per capita consumption of electricity. However, this is not given per-se and complex research has evolved to understand the dynamic changes in electricity consumption after receiving access to electricity. In any case, the variation and potential evolution of electricity consumption remain context-specific. To understand the dynamics of electricity consumption for the case study under investigation, we conduct a trend analysis. Table 1 and Table 2 provide an overview of the evolution of the average daily power demand and electricity consumption for the years 2018 to 2021 in conjunction with the number of households actively using the nanogrid for a given year and the number of days for which data was available. While the only significant change in average power demand can be observed between 2020 and 2021 with a change in the average power demand of approximately 32 %, there is a year-by-year increase in the average daily energy consumption of connected households. The most significant precentual increase can be observed between 2018 and 2019 with an increase of 168%.

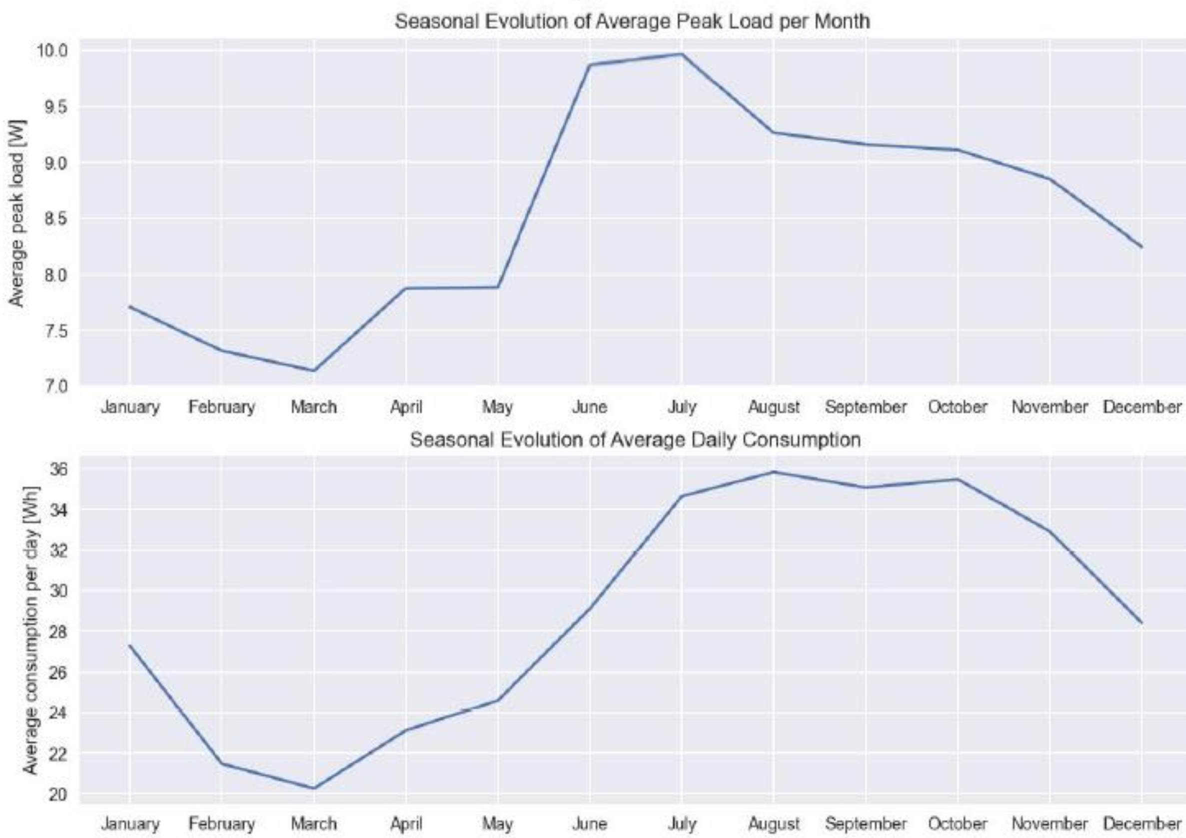
Figure 4 a) illustrates the evolution of the total electricity consumption amongst all clients. A clear overall increasing trend can be observed and is impacted by the commission of new nano grids (indicated as a red dashed line). The trend is not observed in the average peak power consumption amongst clients, which remains stable over the data recorded, see Figure 4 b). However, analysing the electricity consumption in periods with no disturbing new client connections (e.g., January 2021 – June 2021) suggests an increase in the electricity consumption starting after the rainy season (January – April). This trend is supported by analysing the average monthly (Figure 4 c) top) and daily (Figure 4 c) bottom) electricity consumption per client. Both figures show a significant increase in electricity consumption during the months of July – December. This may be explained with the seasonality of crops, potentially increased liquidity of the households during these months, and less hours of sunshine.



a)



b)



c)

Figure 4: a) Evolution of the total client´s average daily electricity consumption over the years. The grey dashed-line indicates the commission of new nano-grids.
b) Evolution of the average daily peak load of all clients over the years.
c) Seasonal variation of the average monthly peak load (top) and electricity consumption (bottom).

Table 1: Evolution of the average daily power demand between the years 2018 and 2021

Year	Number of Days with Data	Number of Households Connected	Average Daily Power Demand	Percentage Change of Evolution of Average Daily Power Demand
[#]	[#]	[#]	[W]	[%]
2018	325	25	2.26	-
2019	365	60	2.25	-0.75
2020	366	96	2.27	0.92
2021	335	101	2.99	32.11

Table 2: Evolution of the average daily electricity consumption between the years 2018 and 1021

Year	Number of Days	Number of Households Connected	Average Daily electricity Consumption	Percentage Change of Evolution of Average Daily Consumption
[#]	[#]	[#]	[Wh]	[%]
2018	325	25	8.16	-
2019	365	60	21.88	168.27
2020	366	96	35.47	62.11
2021	335	101	50.62	42.72

3.1.3.2. Classification

Nano grid clients are charged via upfront payments, which can be conducted remotely. During the payments, the clients can decide on a maximum amount of energy per day, maximum power, and number of credits worth for a day of service to purchase. When exceeding either the purchased amount of electricity, power consumed, or days of energy service, the clients will remotely be cut off from service until re-purchasing further credits. Thus, we must assume that the electricity consumption of clients may significantly be impacted by the subscribed tariff. We, therefore, categorize the clients according to their subscribed tariff. However, a change in tariff over the three years of the data record may be assumed. Further, the tariff conditions may have changed over the last three years. The data only includes the name of the household´s subscription chosen during changes in the tariff, but not the customers' subscription for those who did not change their initial subscription. Thus, we must additionally treat the data to derive the change-in-tariff of clients.

Based on a multi-class classification method (see Annexe 1 theory, background, and detailed application to the case study), we, therefore, seek to identify the electricity tariff subscribed by each household. We, therefore, reduce the option for tariffs to the six most common distinct tariffs out of the 17 tariffs available. The tariffs and respective power and daily energy limits are listed in Table 1.

Table 3: Subscription options included in the analysis.

Tariff Name	Maximum Power (W)	Maximum energy consumption per day (Wh)
Eco	10	50
Eclairage	18	90
Eclairage Plus	30	150
Multimedia	42	210
Multimedia Plus	66	330
Congel	125	1250

We compared the maximum daily consumption of households with the maximum allowed consumption values as referenced in the tariffs, assuming the tariff reference values to indicate sharp thresholds. In practice, however, the energy and power consumption variables can exceed these thresholds without the client being immediately cut-off power supply to some extent. We therefore compared the value taken by the q-th quantiles for power and daily energy consumption data (qE and qP). These quantiles correspond to the household's daily consumption values below which q% of the consumption data falls. qE and qP are therefore adjustment variables of our algorithm. Aiming for the best combination of quantiles (qE, qP) assumed to describe the fit for a specific tariff, we evaluated each possible combination of quantiles using a classification metric, varying them with a step of 0.05 each. We assess the set of possibilities on the known classified population (households having made a change of subscription) with the accuracy and balanced accuracy metrics. Measuring both metrics allowed us to avoid possible class-distribution problems due to imbalances in the population. The best combination of quantiles was then used to predict and classify the population of households whose subscription is unknown. First, the classification algorithm was calibrated on the known population (households who switched tariffs) with the help of classification metrics. Then the optimally parameterized algorithm was used to predict the subscription groups of the unknown population. Knowing this information about the entire study population allows us in a later stage to analyse whether a tariff group is associated with a daily consumption pattern or not.

By adopting the calibration for the classification algorithm, we predict the tariff classes of the remaining population (households that have not changed their initial tariff). The distribution of the known population as well as the distribution of the predicted population in the electricity tariff classes are presented in Figure 5. This visual representation allows us to analyse the distribution of households in the tariff classes according to whether they have changed tariffs. It should be noted, however, that households that have changed tariffs are represented several times on the graph in separate classes.

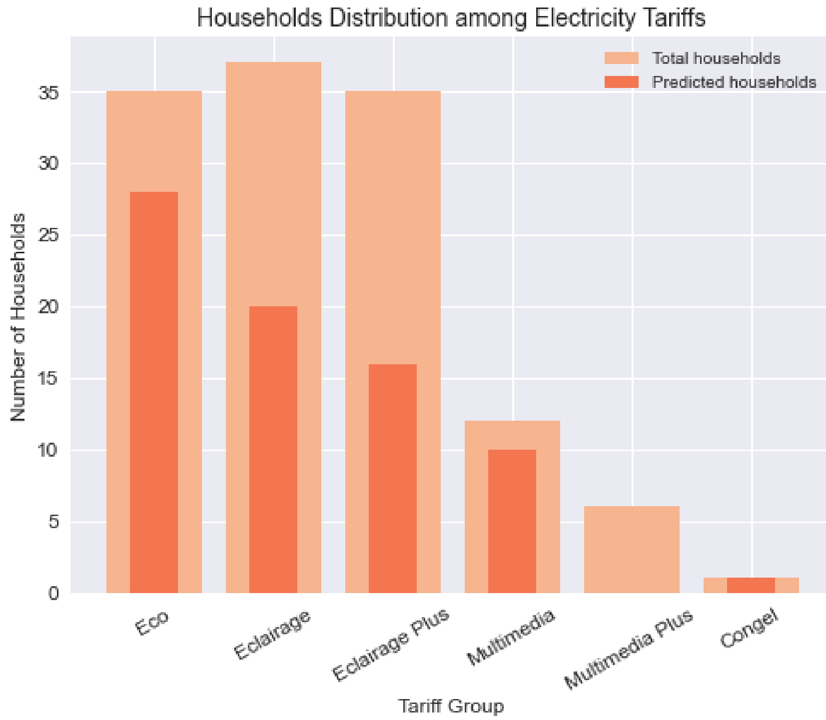


Figure 5: Distribution of households in electricity tariffs.

The data shows that the “Eco” and “Eclairage” tariff classes have the highest total number of households, with 35 and 37 respectively, while the “Multimedia Plus” and “Congel” tariff classes have the lowest total number of households, with only 6 and 1 respectively. Overall, the three lowest electricity tariffs are overrepresented, accounting for 85% of the households, while the three highest electricity tariffs are underrepresented, with only 15% of households subscribing to them. The analysis further reveals that most tariff switches occur between the "Eclairage" and "Eclairage Plus" classes (see confusion matrix in the Annexe 1). Additionally, only 20% of households from the "Eco" tariff switched subscriptions. We must note that for the remaining of the study, the household with a Congel subscription was excluded from the study population because of its outlier nature, especially towards the cluster analysis.

3.1.3.3. Clustering

The overarching framework of the statistical analysis foresees to conduct a cluster analysis on electricity consumption patterns to identify representative group’s electricity consumption patterns. Subsequently, different tests of independency analyse the relation between socio-economic variables and the cluster membership (electricity consumption pattern group) to derive influencers significantly driving the electricity consumption pattern. Background including limitations of the statistical tests applied is given in the Annexe 3.

We applied k-mean clustering analysis to the average daily load curves of households (0). K-means clustering was performed in the Python programming language with the help of the machine learning library *sci-kit-learn.* It features various classification, regression and clustering algorithms including k-means and is designed to interoperate with the Python numerical and scientific libraries NumPy and SciPy. Calculating the silhouette score reveals three clusters to offer the best data partition of the samples. According to the repartition in three clusters, cluster 1 contains most of the consumers with 64.5% of the total studied households, i.e., 69 consumers. Cluster 0 and Cluster 2 share almost equally the rest of the households, with 18 households (16.8%) and 20 households (18.7) respectively.

The individual samples within each cluster differ in the shape and range of their daily electricity consumption profiles. The average (mean) electricity consumption profile of each cluster is illustrated Figure 6.

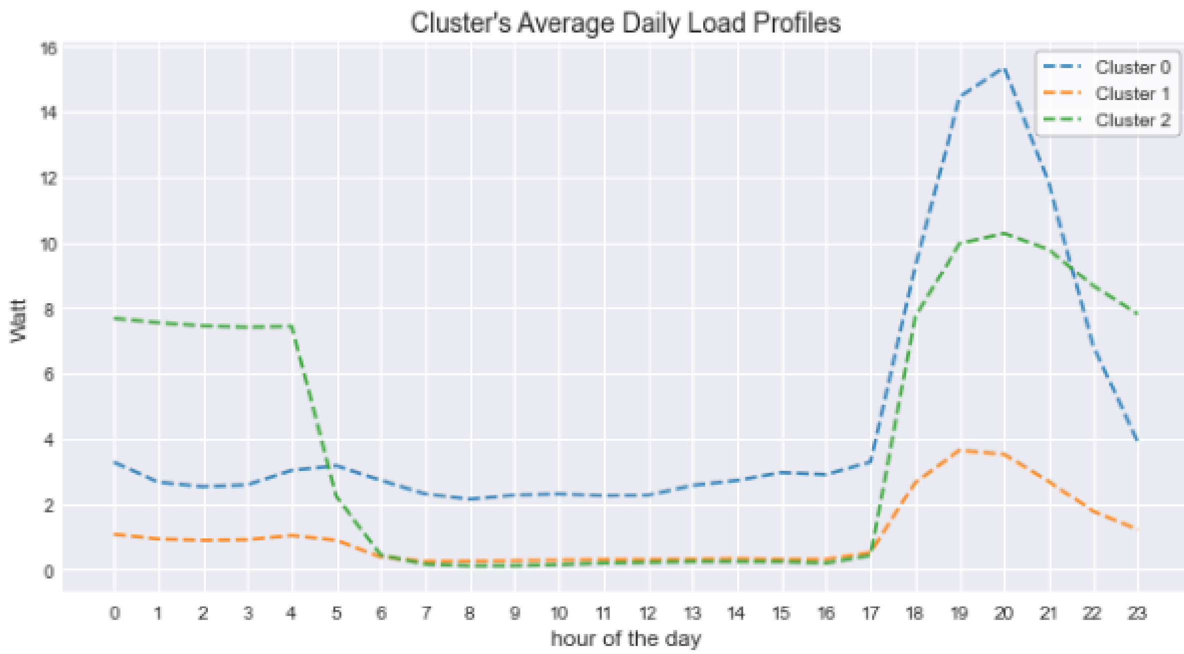


Figure 6: Average electricity consumption profiles of representative households

The electricity consumption profile of households included in cluster 0 is characterized by a relatively high evening (8 pm) peak power demand of ca.15 W, compared to a baseload demand of around 3W during the day. Households of cluster 1, have a low night demand at around 1W, and almost no daytime consumption. However, there is a small evening peak reaching around 4W. Cluster 2 households are represented by a medium-sized evening peak that reaches 10W and medium night consumption at around 8W, and no consumption during the day. We may identify two extreme stereotypes of the consumer; a low-demanding consumer (cluster 1), whose consumption is less than the other cluster´s consumption at any time and less than 4 W in peak, and a high-demand consumer profile, corresponding to cluster 0, with an evening peak demand about 4 times higher than the peak of the low demand consumer and twice that of cluster 2. Over the day, this profile also represents the highest demand with an almost constant medium baseload at 3W, while during the night, cluster 2 shows the highest demand. Figure 7 a) – c) show the respective average daily profiles of each cluster.

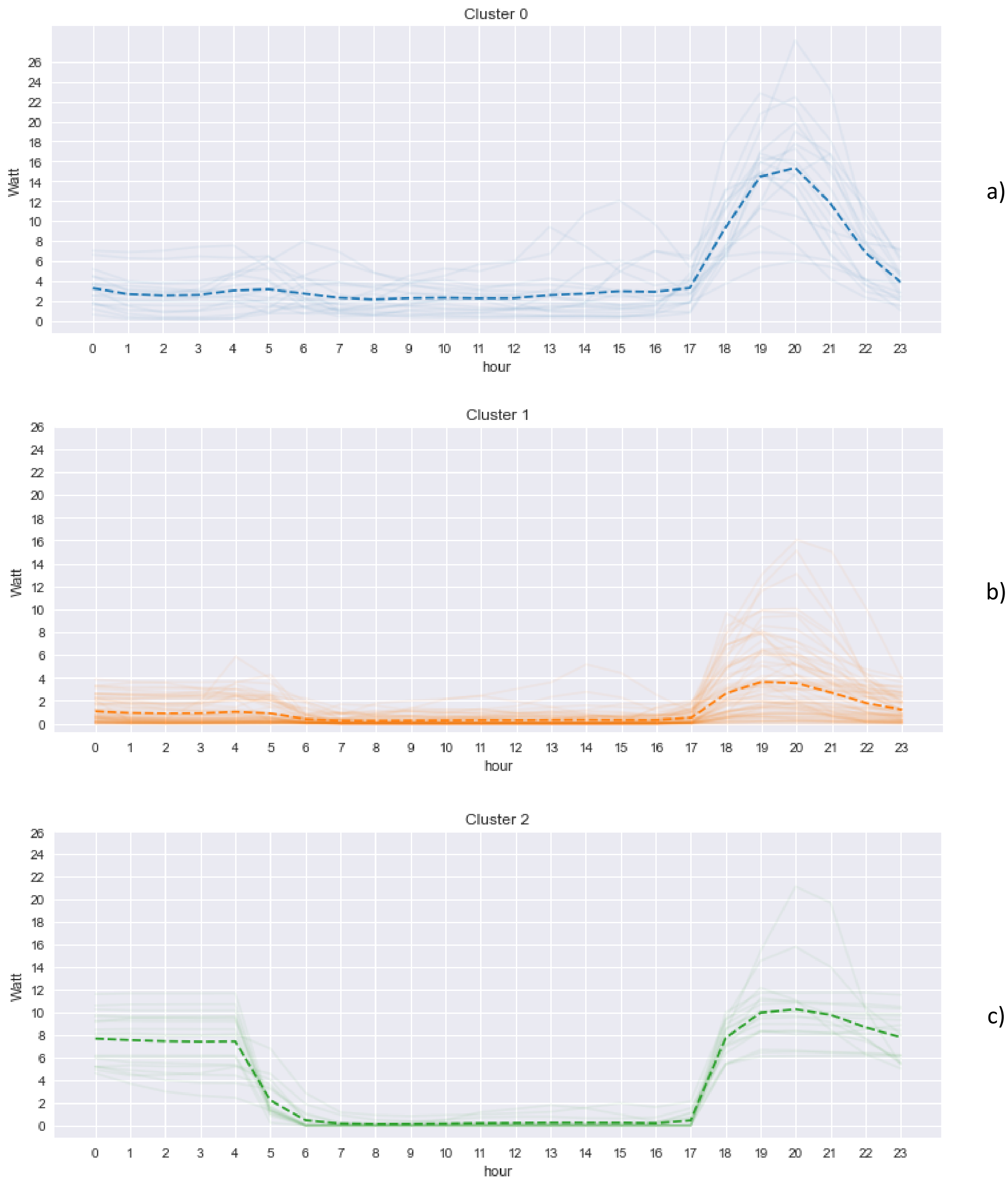


Figure 7: Average daily electricity consumption profiles of households in a) Cluster 0, b) Cluster 1 and c) Cluster 2.

3.1.4. Socio-Economic Influencers of Electricity Consumption

The main objective of the statistical analysis is to understand how energy consumption patterns are influenced by – and can thereby be determined via the study of – socio-economic characteristics and other influencers. Therefore, we aim to detect socio-economic characteristics that significantly influence the energy consumption patterns of the sample group. On the level of our investigation, the findings will be useful to develop different scenarios of community composition (thereby, electricity consumption patterns) to study the integration of PUE within. On a superior level, the findings will allow for a better understanding of potential changes in the energy consumption of individual users, thereby improving the planning of future energy systems.

Socio-economic data of the population was obtained by questionnaires conducted by Nanoé as part of a market survey to detect potential locations for nano grid development. Questionnaires have been conducted amongst 209 people between 01.03.2017 and 03.10.2022. For our analysis, the socio-economic data and electricity consumption data must include origins from the same household. Thus, we reduce the number of households included in our analysis to households currently connected to a nano grid. To ensure that this reduced sample group is representative of the entire village, we compare the descriptive statistics of socio-demographic characteristics, finding no striking deviation between the reduced sample group and the overall population in Ambohimena (Annexe 2: Descriptive Statistical Analysis).

The socio-economic parameter incorporated in our analysis includes electricity tariff, appliance ownership (LED bulb, LED spot, TV, USB phone charger, 12 V plug), occupational status, number of household members, number of adults within the household, number of children within the household, monthly household income, house size, and profession of the client (grouped into a trader, farmer, employee, other, public lighting). Notably, the public lighting function is included in the job groups, as can be seen as functionality to fulfil.

To detect a significant correlation between socioeconomic characteristics and cluster membership, a series of Chi-square and Fisher tests were conducted (see Annexe 3.3 and Annexe 3.4 for theory and background). The tests were conducted in IBM SPSS (Statistical Package for the Social Sciences). Table 2 reports the correlations that are significant, with a p-value < 0.05*.

Table 4: Aocio-economic correlation with cluster groups
EC = Expected count, C = Count.
** statistically significant at p-value confidence level = 0.05*
*** statistically significant at p-value confidence level = 0.1*

Variables		Cluster 0		Cluster 1		Cluster 2 Tariff Groups		Chi2	df	Fisher Exact	p-value	Cramers V
		C	EC	C	EC	C	EC					
Eco*	Yes	1	5,7	31	21,9	2	6,4	15,588	2		<0,001*	0,382
	No	17	12,3	38	47,1	18	13,6					
Eclairage	Yes	5	5,7	23	21,9	6	6,4	0,239	2		0,871	0,047
	No	13	12,3	46	47,1	14	13,6					
Eclairage Plus*	Yes	9	4,7	17	18,1	2	5,2	8,081	2	7,574	0,022*	0,275
	No	9	13,3	52	50,9	18	14,8					
Multimedia*	Yes	7	2	4	7,7	1	2,2	16,654	2	12,316	0,001*	0,395
	No	11	16	65	61,3	19	17,8					
Multimedia Plus	Yes	2	1	4	3,9	0	1,1	2,223	2	1,984	0,313	0,144
	No	16	17	65	65,1	20	18,9					
Public Lighting*	Yes	0	2	1	7,7	11	2,2	47,39	2	33,853	<0,001*	0,666
	No	18	16	68	61,3	9	17,8					
Tariff Switch*	Yes	11	5	17	19,3	2	5,6	13,379	2		0,001*	0,354

	No	7	13	52	49,7	18	14,4					
Appliances Ownership												
	Yes	16	14,1	61	55,7	7	14,1	20,201	2	16,635	<0,001*	0,435
Led Bulb*	No	2	3,9	10	15,3	11	3,9					
	Yes	0	2	1	8	11	2	54,137	2	37,199	<0,001*	0,711
Led-Spot*	No	18	16	70	63	7	16					
	Yes	3	2	8	8	1	2	1,116	2	1,095	0,6	0,102
TV*	No	15	16	63	63	17	16					
	Yes	15	8,9	31	35,2	7	8,9	10,021	2	10,199	0,006*	0,306
USB Phone Charger	No	3	9,1	40	35,8	11	9,1					
	Yes	10	5,7	21	22,6	3	5,7	6,749	2		0,034	0,251
12V Plug (Simple&Double) *	No	8	12,3	50	48,4	15	12,3					
	0	2	3,9	10	15,3	11	3,9	40,883	12	35,687	<0,001*	0,437
	1	6	7,9	40	31,2	1	7,9					
	2	4	4	14	15,9	6	4					
	3	3	1,2	4	4,6	0	1,2					
	4	1	0,7	3	2,7	0	0,7					
	5	1	0,2	0	0,7	0	0,2					
LED Bulb Quantity	8	1	0,2	0	0,7	0	0,2					

Survey Variables

		Cluster 0		Cluster 1		Cluster 2		Chi2	df	Fisher Exact	p-value	Cramers V
		C	EC	C	EC	C	EC					
	free	1	0,2	0	0,7	0	0,1	5,182	4	5,946	0,195	0,181
	owner	14	14,8	54	52,7	5	5,5					
Occupant status	tenant	1	1	3	3,6	1	0,4					
	large	8	4	11	15,2	2	1,8	8,515	4	7,027	0,089	0,226
	medium	8	10,6	42	39,8	5	4,6					
House size	small	0	1,3	7	5,1	0	0,6					
	0	0	0,2	1	0,7	0	0,1	6,689	10	8,661	0,568	0,207
	100000	0	2,5	10	8,6	2	0,9					
	150000	7	7	25	24,4	2	2,6					
	200000	6	4,5	14	15,8	2	1,7					
	300000	2	1,2	4	4,3	0	0,5					
Monthly household income	500000	1	0,6	2	2,2	0	0,2					
	0	0	1	5	3,6	0	0,4	16,766	12	14,922	0,149	0,312
	1	1	0,4	1	1,4	0	0,2					
	2	1	3,4	15	12,3	1	1,4					
	3	8	4,2	13	15,1	0	1,7					
	4	3	4	15	14,4	2	1,6					
Number of household members	5	3	3,6	11	13	4	1,5					

	6	1	0,6	2	2,2	0	0,2				
	0	0	0,8	4	2,9	0	0,3	4,865	6	4,818	0,608	0,169
	1	1	3	13	10,8	1	1,2					
	2	16	13	43	46,6	6	5,4					
Number of adults	3	0	0,2	1	0,7	0	0,1					
	0	1	2,9	13	10,9	1	1,3	16,175	8	13,283	0,065	0,31
	1	8	4,6	16	17,4	0	2					
	2	3	4,4	19	16,7	1	1,9					
	3	3	3,6	11	13,8	5	1,6					
Number of children	4	1	0,6	2	2,2	0	0,3					
					Job Groups/functionality							
	Yes	9	5,4	17	14,8	0	5,8	13,263	2		0,001*	0,429
Trader*	No	6	9,6	24	26,2	16	10,2					
	Yes	8	7,9	25	21,6	5	8,4	4,083	2		0,13	0,238
Farmer**	No	7	7,1	16	19,4	11	7,6					
	Yes	4	1,7	4	4,6	0	1,8	5,751	2	4,959	0,056**	0,283
Employee*	No	11	13,3	37	36,4	16	14,2					
	Yes	0	2,5	1	6,8	11	2,7	40,226	2	31,89	<0,001*	0,747
Public Lighting*	No	15	12,5	40	34,2	5	13,3					
	Yes	1	1,7	6	4,6	1	1,8	1,198	2	0,849	0,676	0,129
Other	No	14	13,3	35	36,4	15	14,2					

Based on the results we can identify such socio-economic characteristics that may predict i) a definite certain cluster membership, representing a certain electricity consumption pattern and ii) the share of the trait within a cluster. As it may be more intuitive, we describe the deviation of the clusters below. The cluster is characterized as follows:

Cluster 0: "average household"

- 50 % of the respondents in Cluster 0 work as traders, compared to 25 % in Cluster 1 and 0 % in Cluster 2.
- 61% of the respondents in cluster 0 have changed their tariff since the date recording, compared to 25% and 11% in cluster 1 and cluster 2, respectively.
- The "Multimedia tariff" is the most prominent tariff option chosen from cluster 0 respondents with 35% (compared to 5% each in cluster 1 and cluster 2). The "Eco" tariff is underrepresented with only one respondent indicating to have opted for the tariff. No "public lighting" tariff is identified.
- Households in cluster 0 report the highest number of LED bulbs (2.2), with 89% of the respondents having at least one light bulb. 83% of the respondents indicate owning a phone charger, compared to 45% and 35% in cluster 1 and cluster 2 respectively. 56% of cluster 0 respondents own 12V plugs.

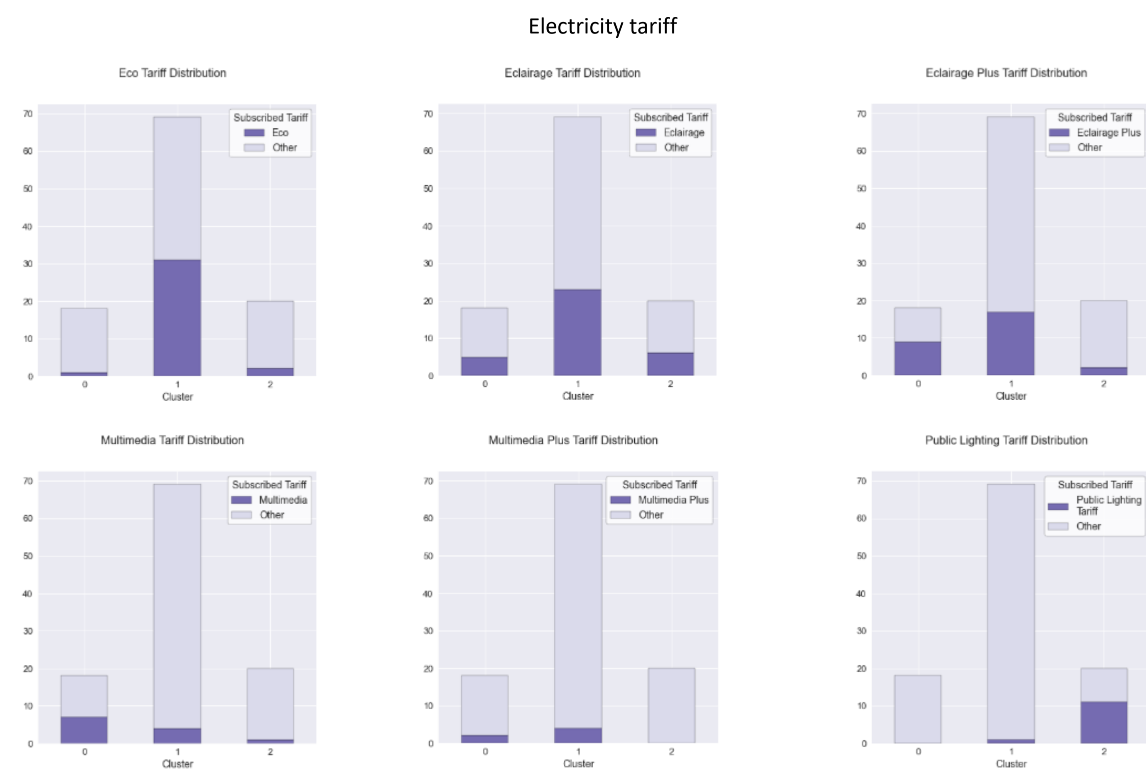
Cluster 1: "Low-consumption"

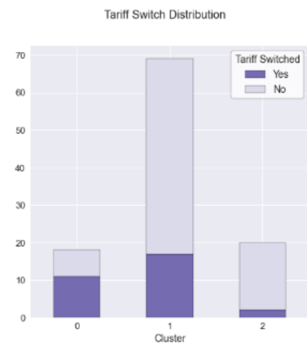
- Cluster 1 households account for 97% of the total households with an “Eco-tariff”. 45% of the respondents from cluster 1 choose the eco-tariff, and only 5.6% the multimedia tariff. 25% of the households have switched the tariff, compared to 61% Cluster 0 and 11% in Cluster 2.
- While 88% of the respondents in cluster 1 own at least one LED bulb, the average number of LED bulbs per household is the lowest (1.3). 44% of the respondents own a phone charger, 30% own 12 V plugs.
- Most of the respondents (36%) of cluster 1 are farmers, while 24% are traders.

Cluster 2: “public lighting”

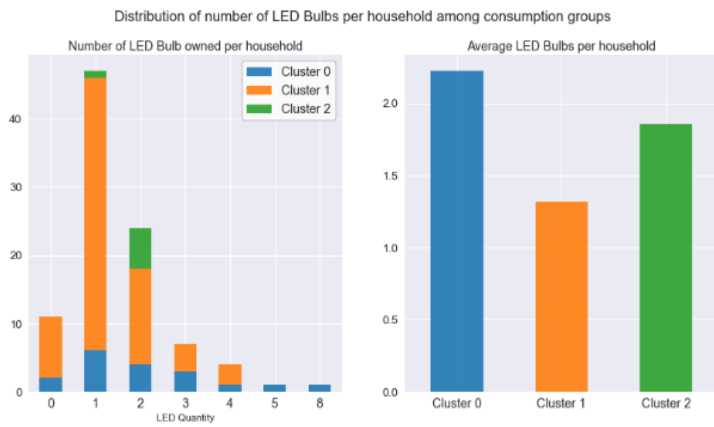
- Cluster 2 accounts for 11 out of the total 12 respondents with a “public lighting tariff” (thus 11 out of the 12 LED spots registered). 55% of the responding clients in cluster 2 report to have chosen the “public lighting tariff”, while 30% “Eclairage” 10% “Eco” and 1% “multimedia” tariffs have been recorded. 11% of the households have switched the tariff.
- Aside the 11 public lighting functions, 5 respondents of the cluster 2 are farmers. No employees and traders are listed amongst the jobs.
- Aside LED spots (55%), 35% of the respondents of cluster 2 report to have at least one LED bulb and a phone charger. 17% report to own a phone charger.

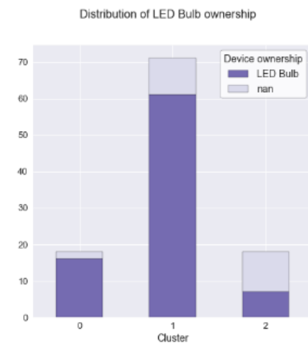
To illustrate, the descriptive statistics of the socio-economic parameters distributed across the different clusters is provided in Figure 8.

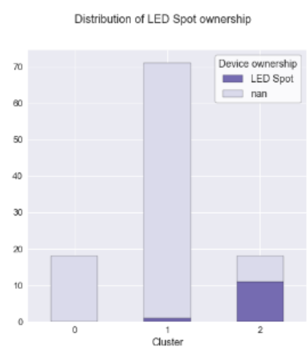


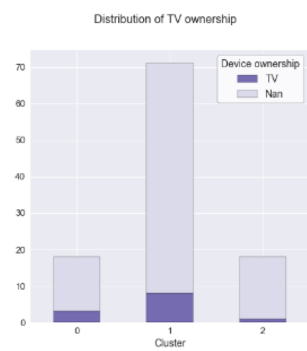


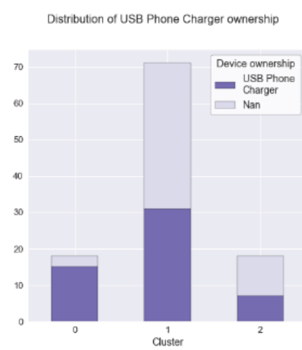
Appliance ownership

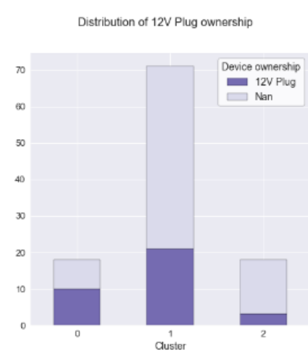




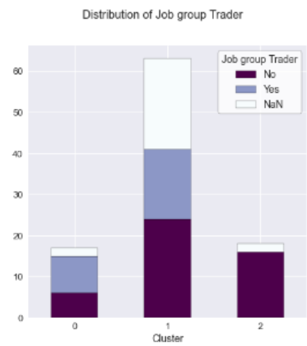


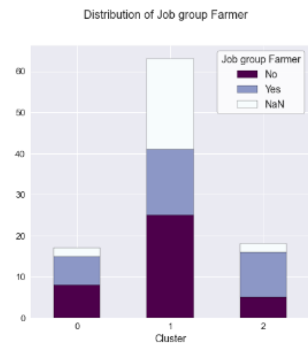


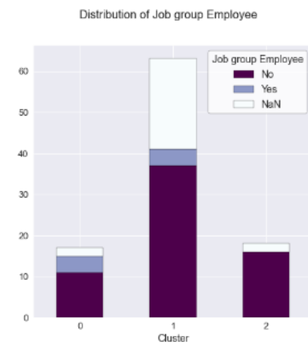


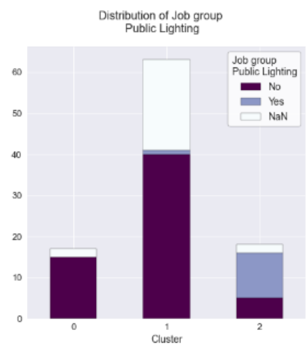


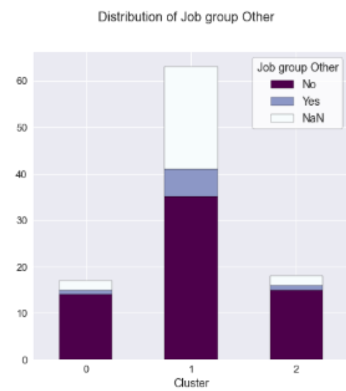
Employment



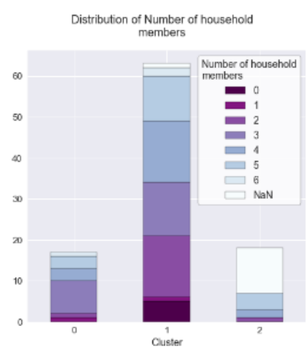


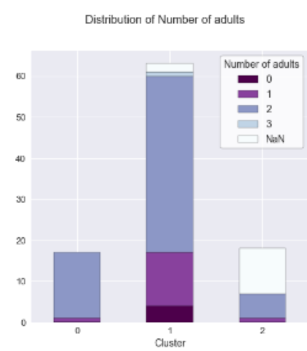


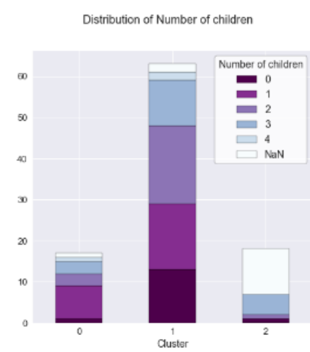




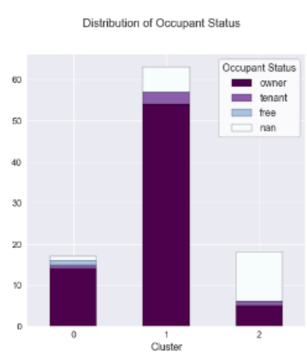
Household size

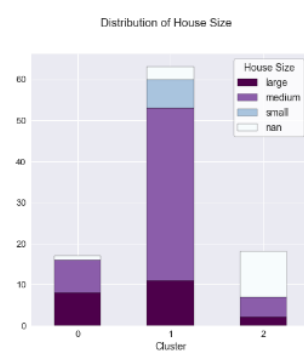






Housing





Income

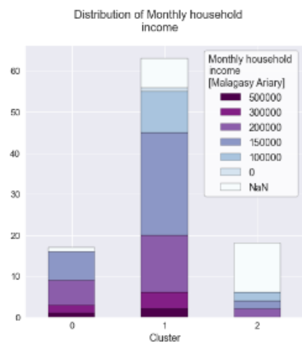


Figure 8: Descriptive statistics of the socio-economic parameter distributed across the three detected clusters.

We conclude on the treatment of energy consumption data and statistical analysis of socio-economic and energy consumption data to develop suitable scenarios for energy system modelling in a later stage:

- The residential energy consumption is influenced by a seasonal variation, with an increase in consumption towards the winter month (July - December)
- Three distinct representative types of electricity consumption patterns can be identified. We stereotype them as "average household" (cluster 0), "low-consumption" (cluster 1) and "public lighting (cluster 2).
- Significant predictors for a cluster membership - thereby significant influencers for the energy consumption pattern - are:
- type of tariff, if "Eco", "Eclairage Plus", "Public lighting", "multimedia" and the switch of tariffs
- Appliance ownership, indicative if owning "LED bulbs, LED spot, TV, 12 V plug.
- Job group or functionality, if indicated as a trader, farmer, employee, or public lighting.

3.2. Techno-Economic Evaluation of PUE Integration

The overall objective of the case study analysis is to provide insights into the impacts of the integration of PUE on system and a community level. In the previous section, the relation between the consumption behaviour of households in Abohimena and socio-economic characteristics was analysed in detail and consumption scenarios were defined. The consumption scenarios serve as an input for the optimization of energy system models that represent different PUE-integration scenarios, the development of which is described in this section. The consecutive steps taken in the development of the set of energy system models are depicted in Figure 9.

The initial step in the development of energy system models reflecting different approaches to PUE integration consisted of the selection of the PUE to be included in the case study analysis. After further specifying the research questions and identifying relevant information to be gathered, interview guides were developed and tested. Subsequently semi-structured interviews were conducted as part of a field trip to the demonstrator region and the case study location. The interviews served the purpose to learn about the status quo of the selected productive uses and to gather all relevant information to specify relevant integration scenarios and design the respective energy system models. For the development of the PUE-integration, besides the results from the interviews conducted, additional data provided by Nanoé was taken into consideration. As the final step, the energy system models were developed utilising the interview results, the previously developed fundamental energy system models (Task 1.2.3) and additional economic data provided by Nanoé.

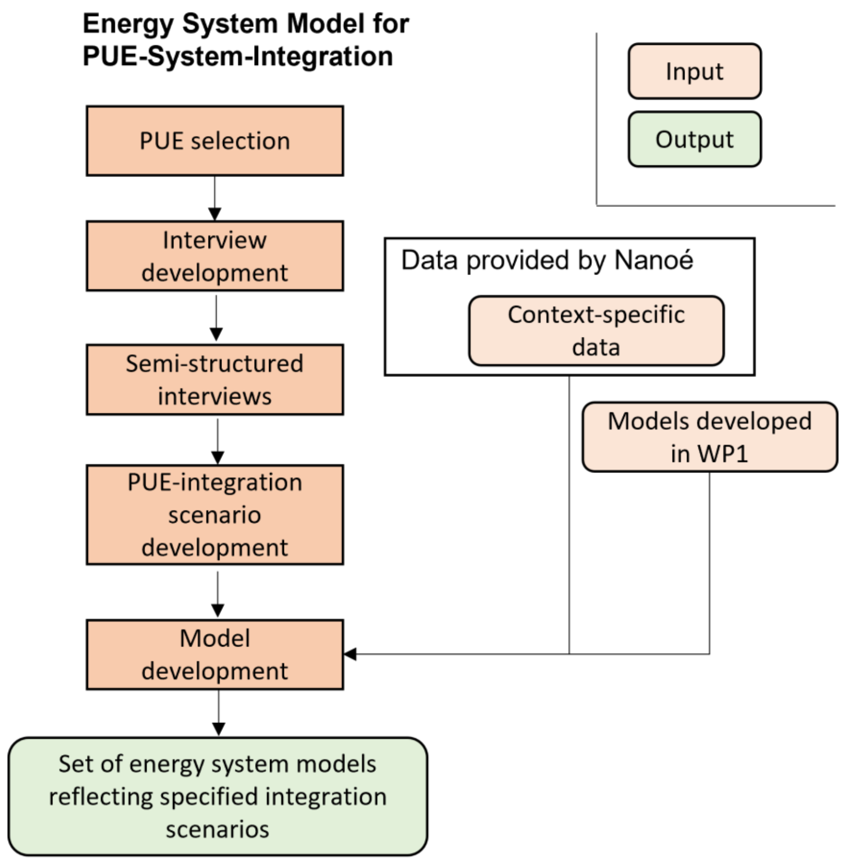


Figure 9: Working scheme for the development of energy system models for PUE-system integration.

3.2.1. PUE Selection

The initial selection of PUE of interest was determined by the selection of PUE included in the ENERGICA project. The PUE to be investigated as part of this case study were decided on in collaboration with Nanoé during a field trip in October and November 2022 in the Ambanja district. The PUE were selected according to their current dominance and importance in the local value chains and the potential integration into the nano grids of Nanoé. The two PUE selected for further investigation as part of the case study analysis are (1) Rice processing and (2) Decentralized ice production. A market assessment of the PUE was conducted during the field trip in 2022.

3.2.2. Field Visit and Semi-Structured Interviews

With regard to the case study analysis, the main objective of the field visit and the conducted interviews were to gain a general understanding of the energy landscape in the case study location, gain in-depth knowledge about the status quo of the productive uses of interest, including the product and value flows they entail within the community and to obtain qualitative and quantitative data for the description of PUE-integration scenarios and they representation in the form of energy system models. In the following, first semi-structured interviews are introduced as a tool for information acquisition, the development of the interview structure is explained and finally an overview of the interviews conducted is provided.

3.2.2.1. Method Selection

The underlying objectives require an in-depth understanding of the context and semi-structured interviews were determined to be a suitable method for data collection. Stakeholder interviews, which include semi-structured stakeholder interviews, can be utilized to gain insights into complex correlations of issues [6]. Furthermore, this method of data collection is suitable to portray complete processes and provides comprehensive perspective on a research subject [7]. Stakeholder interviews vary in the degree to which questions are predefined. A semi-structured format with open-ended questions was selected to ensure the required information can be obtained, while still allowing enough freedom to explore emerging topics.

3.2.2.2. Interview Development

The initial steps of the interview preparations consisted of (1) the definition of the scope of the interviews, and (2) the development of the interview instruments. The scope was primarily determined by the content and the logistics of the interview. Content-wise the scope of the interviews resulted from the information base that was required, firstly to comprehensively understand the status quo of productive uses the respective value flows it entails, and secondly to define integration scenarios and enable the development of energy system models. Logistically the scope was determined by the geography of the project demonstration location in Madagascar and the interviewees reachable in a reasonable time. Both the transportation and the coordination with interviewees was initiated and organized by Nanoé. Following the definition of the scope, the interview instruments were developed. The interview instruments included a document specifying the rules of the interview, namely the interview protocol and the interview guide that was used to conduct the interview. Following the guidelines of Witzel [8], the interview guide was developed systematically to enable an analytical and comparative approach, which reflects the researcher's background, without dominating the interview.

While separate interview guides for each PUE were developed, to reflect the particularities of each technology, the subordinate structure of the interview guide is consistent. The interview guide is structured into three main parts: (1) Introduction, (2) Ownership and value streams, and (3) Personal Experience. In the introduction part, the scope, and the context of both the ENERGICA project and the interview to be conducted are shared, and questions of consent are addressed explicitly. The second part contains further structures into three questions categories, namely financing, operation and product flow. The primary objective of this part is to portray a comprehensive picture of the technology ecosystem and the product and value flows it entails, and to understand the economical and operational constraints for the operation of the technology. In the last part of the interview guide, the interview questions address the personal experience of the interviewees and contain questions regarding common problems with the technology and ideas for improving the technology.

As an example, the interview guide developed to interview owners and users of rice hullers is included in the (Annexe 4). As the interviews were conducted in a semi-structured format, the question in the interview guide was starting points and additional questions were asked tailored to the course of the interview.

3.2.2.3. Conducting Interviews

All interviews were conducted during a field trip to the demonstrator region in Madagascar at the end of 2022. Nanoé contacted potential interview partners and coordinated the interview set-up. All interviews were conducted in the Diana region in locations that were reachable from Ambanja within one day. The interviews were conducted by a research team, made up of four members (interviewer, person taking notes, two translators) and the interviewees were owners or operators of PUE. The questions were asked in English, and translated into French by a Nanoé employees, and further translated into Malagasy by a local Nanoé-entrepreneur. Before the interview, the purpose, content, and methodical approach were explained, and the interviewees were given the opportunity to ask questions and ask for clarifications. Furthermore, interviewees were informed that they can skip questions and sections of the interview. In line with the recommendation of Marshall and Rossman [9], care was taken to conduct the interviews neutral, to not bias the answers given. The documentation of the interviews was anonymised.

The following table (Table 5) gives an overview of the interviews conducted. In total eight interviews were conducted.

Table 5: Overview of interviews conducted during the field visit.

Interview #	PUE category	Setting	Activity
1	Ice production	Village	Decentralized ice production
2	Ice production	City	Large-scale production of ice
3	Ice Utilization	Rural road	Cooling services and cooling of products to be sold
4	Ice Utilization	Coastal village	Cooling of fish
5	Ice Utilization	Coastal village	Cooling of fish
6	Rice Processing	Village	Rice processing services
7	Rice Processing	Village	Rice processing services
8	Water Pumping	Village	Water system for health clinic

3.3. Status Quo of Productive Activities

Based on the insights of the interviews and information provided by Nanoé, the current productive activities which may be improved by the integration of electric PUE were analysed with regards to the existing value streams. Below, a short description of the current productive activities is given.

3.3.1. Rice Husking

Rice is the staple food in Madagascar and regularly consumed in every meal of the day. Accordingly, many rural villagers are rice farmers, and few process rice. The distribution of rice hullers varies with the population density. However, it is likely that in every larger village at least one rice huller exists, while in more dispersed regions one rice huller is used for many surrounding small villages (“within one valley”). Figure 10 present some typical rice hullers seen during the site visit.

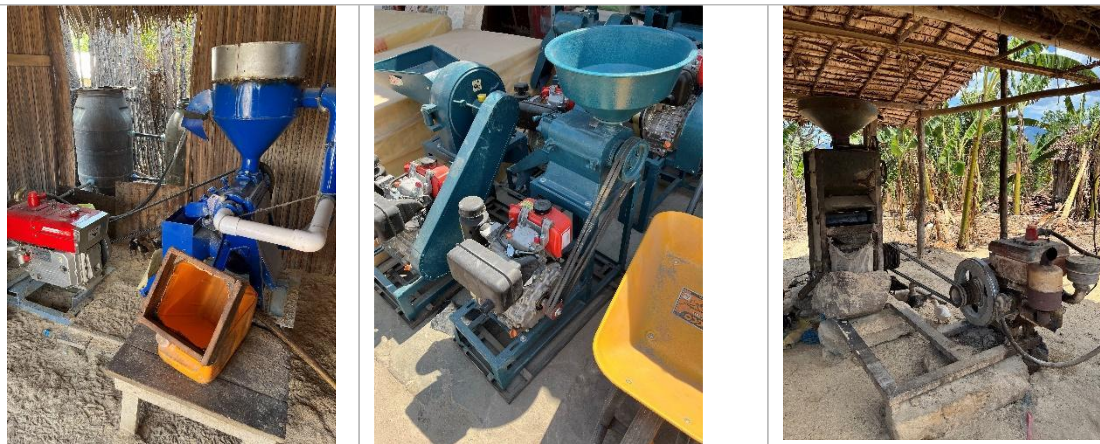


Figure 10: Typical rice processing machines seen during site visits in November 2022 in Ambohimena (left), market in Ambanja (centre), and rural village in Ambanja district (right).

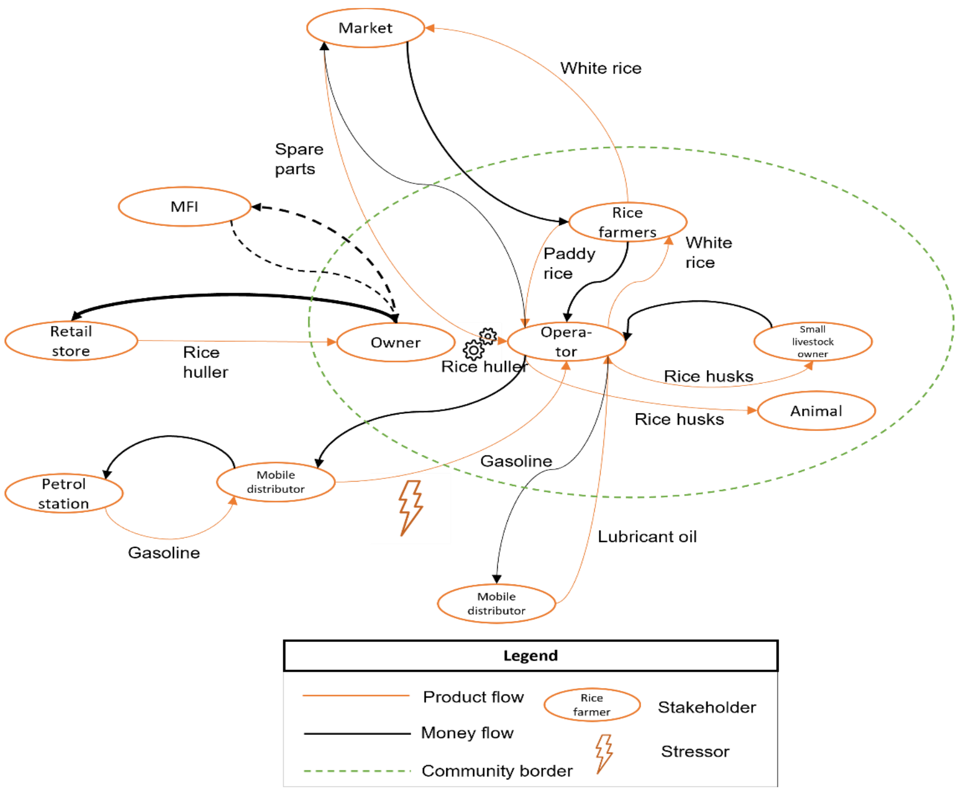


Figure 11: Product and value flow of the current situation associated to rice.

Putting the rice huller at the centre, Figure 11 drafts the product and value flows currently associated with the product rice. The rice huller itself is usually powered by a gasoline engine. Average values of technical and economic parameters assessed via questionnaire conducted by Nanoé amongst 11 rice huller owners are presented in Table 6.

Table 6: Average technical and economic parameter of current gasoline-powered rice huller.

Parameter	Unit	
Technical parameter		
Gasoil consumption	kg_{Paddy}/l	195
Capacity	kg_{Paddy}/h	479,6
Lifetime	Years	5
Year of purchase	/	2016,3
Average annual white rice production	kg/y	48,856

Average annual husk production	kg/y	39,937
Economic parameter		
Purchase price	€	829
Charge for hulling	€/kg Paddy	0,01
Charge for husks	€/kg	0,03
Gasoil price	€/l	0,75
Oil change price	€/l	1,86
Lubrication [-]	€	0,42
Sieves costs [-]	€	5,98
Average annual expenses	€	843
Average annual revenue	€	1,846

The rice huller is purchased at a local market (Ambanja) via one-time payment. Commonly, micro-finance institutes (MFIs) loan money to owners for the initial investment. The huller may be operated by the owner, or by other persons, such as community members. The operator of the huller is paid for the service of processing paddy rice, delivered by local rice farmers. Additionally, the husks (by-product) can be either sold to small livestock owners or fed to own animals like chicken. Spare parts, i.e., sieves are purchased on the market of Ambanja, ca. 1 h traveling by motorbike. Lubricant oil can often be purchased from mobile distributors, reselling lubricant retrieved from petrol stations in Ambanja. The gasoline used to operator the engine can as well be purchased by mobile distributors either, or in the city of Ambanja.

As rice growth depends on the water availability and duration of sunlight, the amount of rice delivered by local farmers to be processed varies over the course of the year. While in May and June the rice huller is heavily utilized (during 6 – 11 am and 2 – 4 pm), especially in February, March, September to November rice harvest is low. Therefore, expenses and revenues of rice huller operator vary significantly. Minimum monthly expenses occur in February, March, September to November (35€/month). Average annual revenue of rice huller owners is 1,846€, with maxima of 405€ per month in May and June. With that, the average daily income of a huller operator is 5€, with 13€ maximum and 1€ minimum. The average annual expenses without depreciation amount to 843€.

During semi-structured interviews, the interviewees highlighted three stressors within the current system.

1. Fuel costs: While fuel was available at any time in the past, the interviewees were concerned about a significant current increase in the fuel price. One interviewee reported an increase of the fuel price by 40% in the last two weeks. While the average gasoil price in 2021 was reported with 0.75€/l, prices in November 2022 were approximately 1 €/l.
2. Rain: Rice requires high and stable amount of water supply for growing. However, the interviewees have noticed decreasing rain falls during the last years, which has impacted the harvest.

3. Ease-of-use: While the interviewees were in general satisfied by the little maintenance the current rice huller requires, the initial start of operation was reported to be a physically exhausting process.

3.3.2. Ice Making and Distribution.

Ice blocks are a main good traded and used in the Ambanja district. The ice is important to maintain a cooling chain for other goods, especially fish, and to support small businesses such as grocery stores that offer cooled beverages. Figure 12 illustrates the current product and value streams associated to ice blocks in the surroundings of Ambanja.

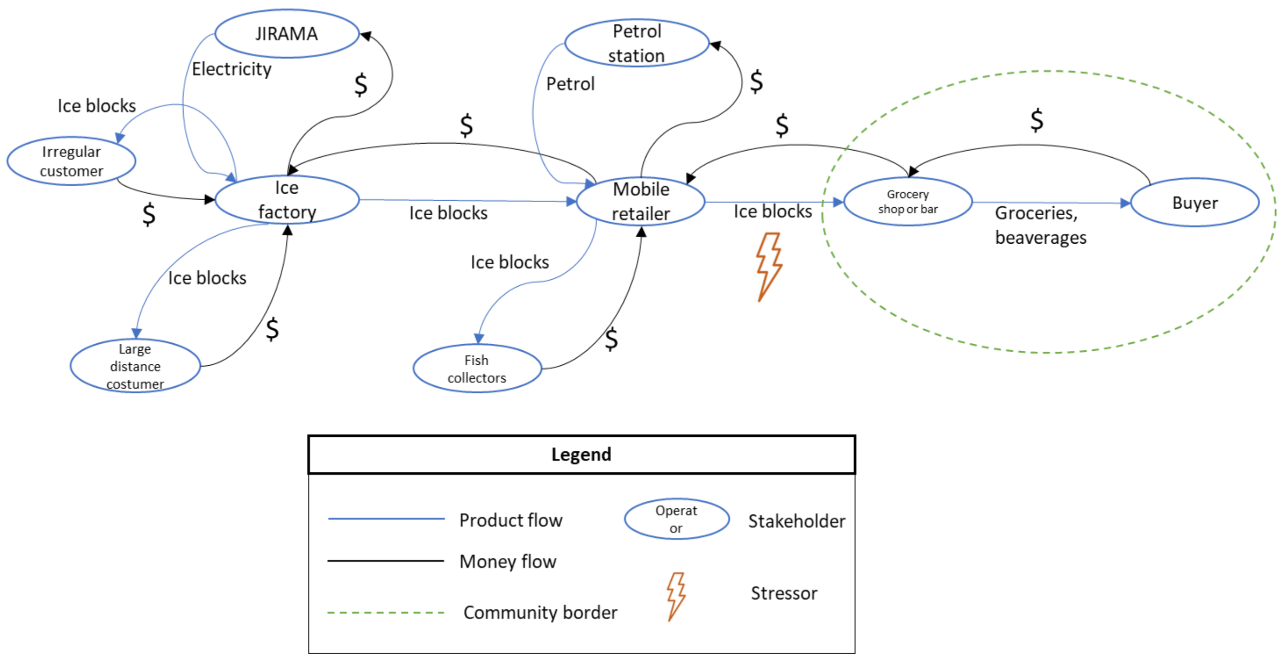


Figure 12: Product and value flow of the current situation associated to ice blocks.

Typically, people use ice blocks to run their business rely on the delivery of ice produced in large ice factories, which are based in Ambanja. The ice factories are diesel-powered stations of different types or rely on electricity supply by the state-owned utility (JIRAMA), see e.g., Figure 13a) and b). These are usually owned by individual investors. The ice blocks produced in Ambanja are mainly purchased by mobile retailer that supply people in the surrounding of Ambanja running a business, e.g., fish collectors or stationary small grocery stores and bars.

Typically, small grocery stores in the rural surroundings of Ambanja own non-functional freezers that still may isolate and allow to cool beverages and food when regularly filled with ice blocks. While the businesses and associated value chains may significantly vary with the size of the business, village the business is in, and distance to Ambanja, a representative pub and grocery store was visited during the field trip in 2022 to interview the operator. The business was located approximately 30 - 45 minutes by motorcycle northern of Ambanja at a main road. The business owns a non-functional freezer, as illustrated in Figure 13 c) and d) and would open every day of the year. The freezer must be filled with ice blocks delivered from mobile Tuk-tuk distributor from Ambanja. Depending on the quality of the ice block, a 10 kg ice block maintains either one or two days. The costs for the ice blocks vary with the season; between

4000 AR (0.83 €) for a 10 kg bar in the rainy season (mid-January – mid-March) up to 6000 AR (1.25 €) in the dry season. The ice is mainly used to cool beer (delivered via mobile distributor in Ambanja as well), while only occasionally used to cool personal belongings, such as vegetables. The business operator stated to sell on average 15 beers per day (minimum two, maximum 40 – 60) with some special occasions during the year. The operator makes a profit of 1150 AR (0.24 €) per bottle buying the bottle for 2850 AR (0.83 €) and selling for 4000 AR (0.83 €). Assuming an average sale of 15 bottles of beer and neglecting sales of other groceries, the average revenue per day is 1,2150 AR (2.52 €) during dry season accordingly.

During the interview, the interviewee stated that the current dependency on ice blocks poses stress to the business. Further, the lack of ability of cooling hinders from diversifying the product range to more lucrative products. Desired new products to cool when owning the appropriate cooling capacities would especially include to offer cooled ice water for Khat users (Khat is a plant containing alkaloid cathinone, a stimulant. Khat chewing is very common in northern Madagascar). Further selling yoghurt or ice cream would potentially be attractive.

a)

b)

c)

d)

e)

Figure 13: a) Modern ice factory in Ambanja.
b) Diesel generator powering the ice factory in a)
c) Typical not working freezer used to cool beverages and food in small grocery stores close to Ambanja
d) Inside the non-working freezer in c)
e) Fish collector using ice blocks to cool fish collected from fishermen and transport to the market in Ambanja.

3.4. Scenario Modelling

The scenario modelling follows the main objective to analyse the compatibility of PUE integrated in the residential energy systems, with respective to different residential electricity demand patterns caused by underlying socio-economic and external factors. We therefore make use of an energy system modelling framework, in which we model different set-ups and scenarios of energy systems, reflecting a specific combination of PUE and residential households. The energy system modelling is applied to optimize for least-cost energy system, including investment and operation. Therefore, a linear optimization problem was implemented in a model, built on the python-based Open Energy Modelling Framework (oemof). The objective function of the linear problem formulated is to minimize the total annualized energy system costs. For a description of oemof and underlying functions, see the Annexe 5 and detailed literature in [10].

Following the workflow drafted in Figure 20, a set of energy system models reflecting the integration of PUE in a residential nano grid will be developed. Subsequently, the residential demand will be varied according to representative consumption scenarios reflecting the identified socio-economic driven consumption patterns of residential clients in (2.1.4). In addition, the PUE electricity consumption data will be modified to reflect a potential change in the user behaviour.

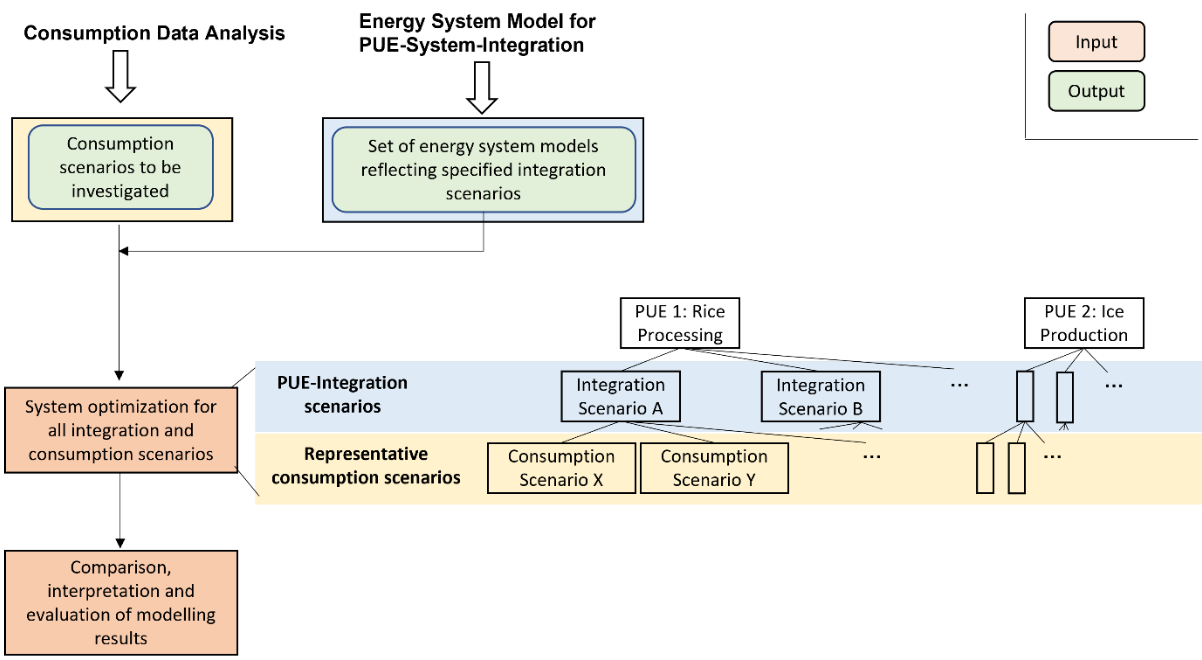


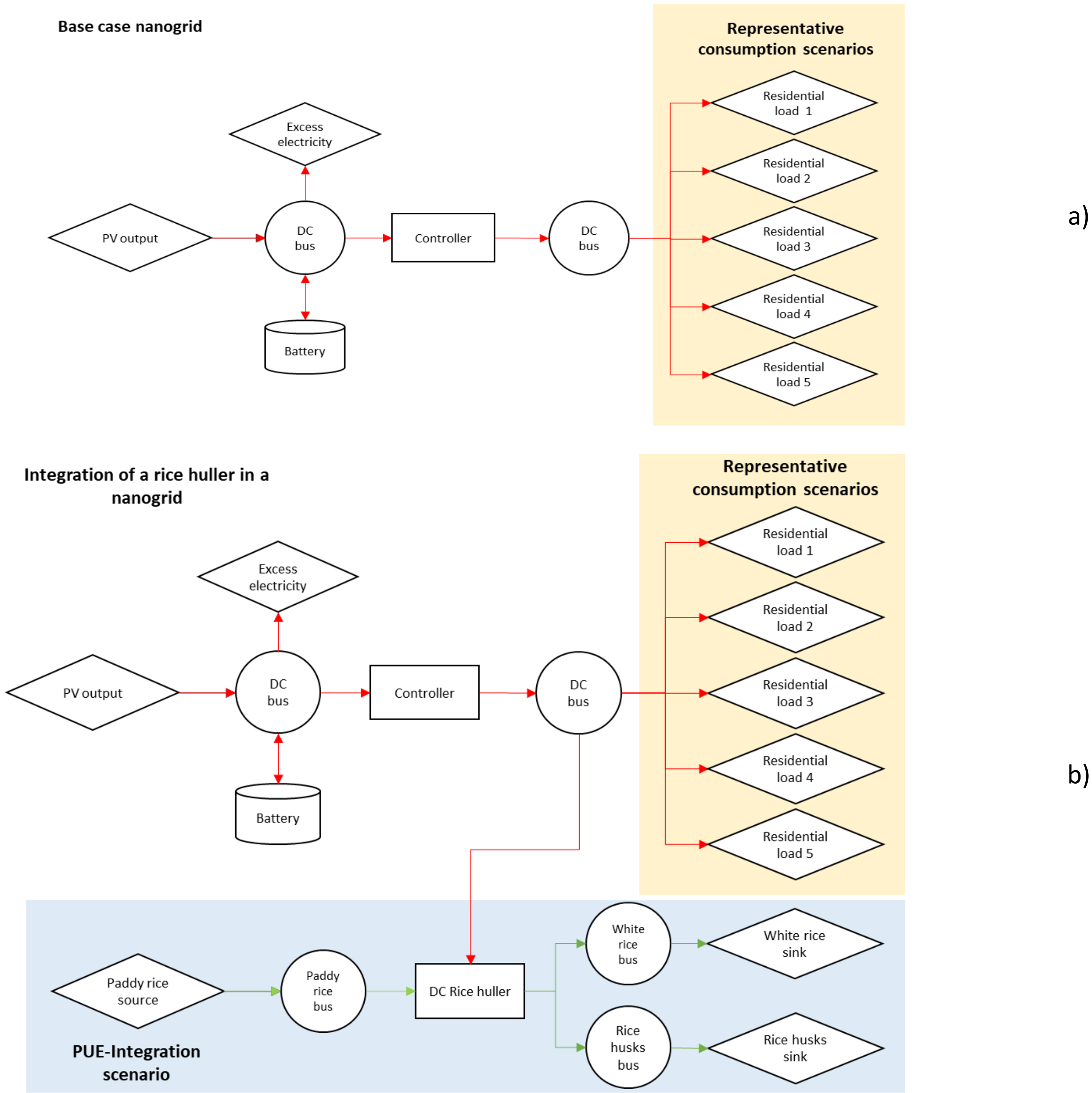
Figure 14: Workflow of the scenario modelling.

For the purpose of the scenario modelling, we define a representative composition of residential loads, which consist of the average profiles of clients in the respective electricity consumption pattern profile cluster identified in section 3.1. In any scenario, we assume five domestic clients to be connected to the nano grid (rounded average). The composed residential electricity profiles are labelled:

- "Representative demand": five residential loads, including three cluster 1 loads ("low-consumption") as the most common cluster, one cluster 0 load ("average consumer) and one cluster 2 ("public lighting")
- "Low demand": five residential loads of cluster 1 ("low-consumption")

- "High demand": five residential loads of cluster 0 ("average household")
- "Low demand with public lighting": four residential loads of cluster 1 ("low-consumption") and one load with cluster 2 profile representing public lighting.
- "High demand with public lighting": four residential loads of cluster 0 ("average household") and one load with cluster 2 profile representing public lighting.

These five distinct residential load scenarios are integrated into the energy system model including the PUE. Thus, the below drafted energy systems are established, see Figure 15.



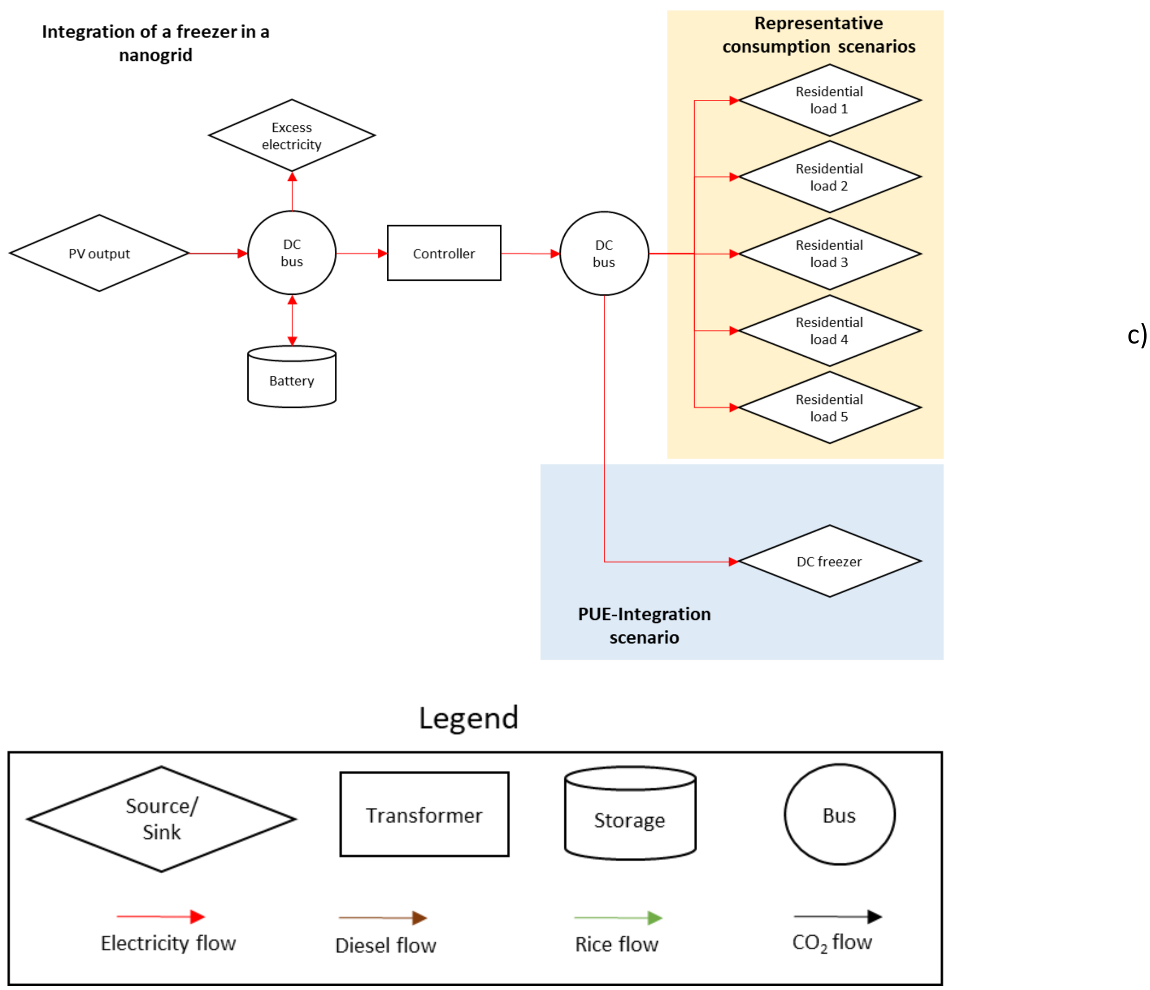


Figure 15: Scheme of the energy system models investigated in our study. For a description of the modelling framework used and representation of classes depicted in the Legend, see the Annex 5.
a) Base case of a residential nano grid.
b) DC-rice huller integrated in a nano grid.
c) DC freezer integrated in a nano grid.

Figure 15 a) illustrates the base case of a nano grid only supplying residential loads. The scenario modelling will be limited to the variation of the representative residential consumption profiles as described above. The results will serve as benchmarks to compare the integration of PUE in the systems. Similar, Figure 15 b) illustrates the rice huller integrated into a nano grid. In the case of integrating a DC rice huller, we will differ between a scenario in which the rice huller follows the operational patterns of current diesel-based rice hullers, and a scenario in which we allow for a maximum of operational freedom that only requires to meet the annal demand for white riced while not constraining the time of output. Notably this scenario does not represent the reality but artificially assumes the storability of rice and not time-bound demands. As especially the latter assumption is unlikely to occur in the reality, the scenario must be understood as an imaginary extremum to compute the potential of granting flexibility to the operation of the rice huller. Figure 15 c) represents the integration of a DC freezer into a nano grid, which may be compared with the base case of a nano grid, and the integrated of a rice huller in a nano grid to compare both PUE. The key technical and economic parameters of the components are listed below in Table 5.

Table 5: Technical and financial assumptions for system components

Component	PV
Lifetime	10 y
Optimal tilt	-29°
Loss fraction	10%
Component	Battery
Lifetime	3,5 y
Efficiency	0,8
SOCmin	0,3
C-rate	0,1

Component	DC Rice Huller
Lifetime	5 y
Conversion rate electricity–>rice flour	70 kg/kWh
Component	DC Freezer
Lifetime	10

	CAPEX fix	CAPEX variable	OPEX	Fuel cost
PV	101 €	540 €/kW	14 €/kW/y	-
Battery	26 €	246.45 €/kWh	14 €/kW/y	-
Supplementary components	306 €	-	9.2 €/y	-
DC Freezer	1 220 €	-	-	-
DC Rice Huller	-	607 €/kW	28 €/kW/y	-
Diesel Rice Huller	-	1.73€/kg_{paddy}/h	0.76 €//kg_{paddy}/h	0.75 €/L

A thorough description of the productive uses can be found in Deliverable 4.1. In this analysis, the load profiles of the PUE were estimated based on the findings of the interviews conducted, and analysis of consumption data provided by Nanoé. Figure 16, Figure 17, and Figure 18 shows a representative daily profile of the PUE load curves.

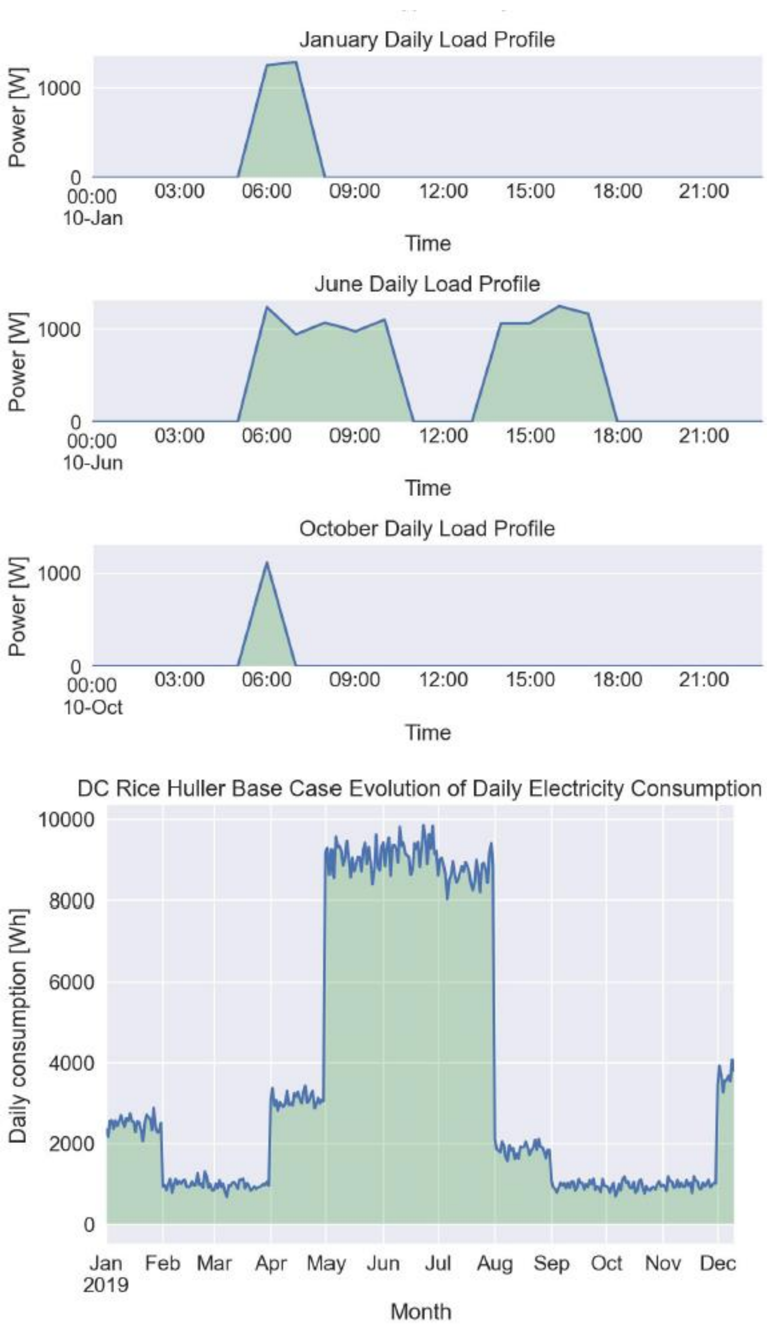


Figure 16: DC Rice Huller Base Case - Typical Daily Load Profiles

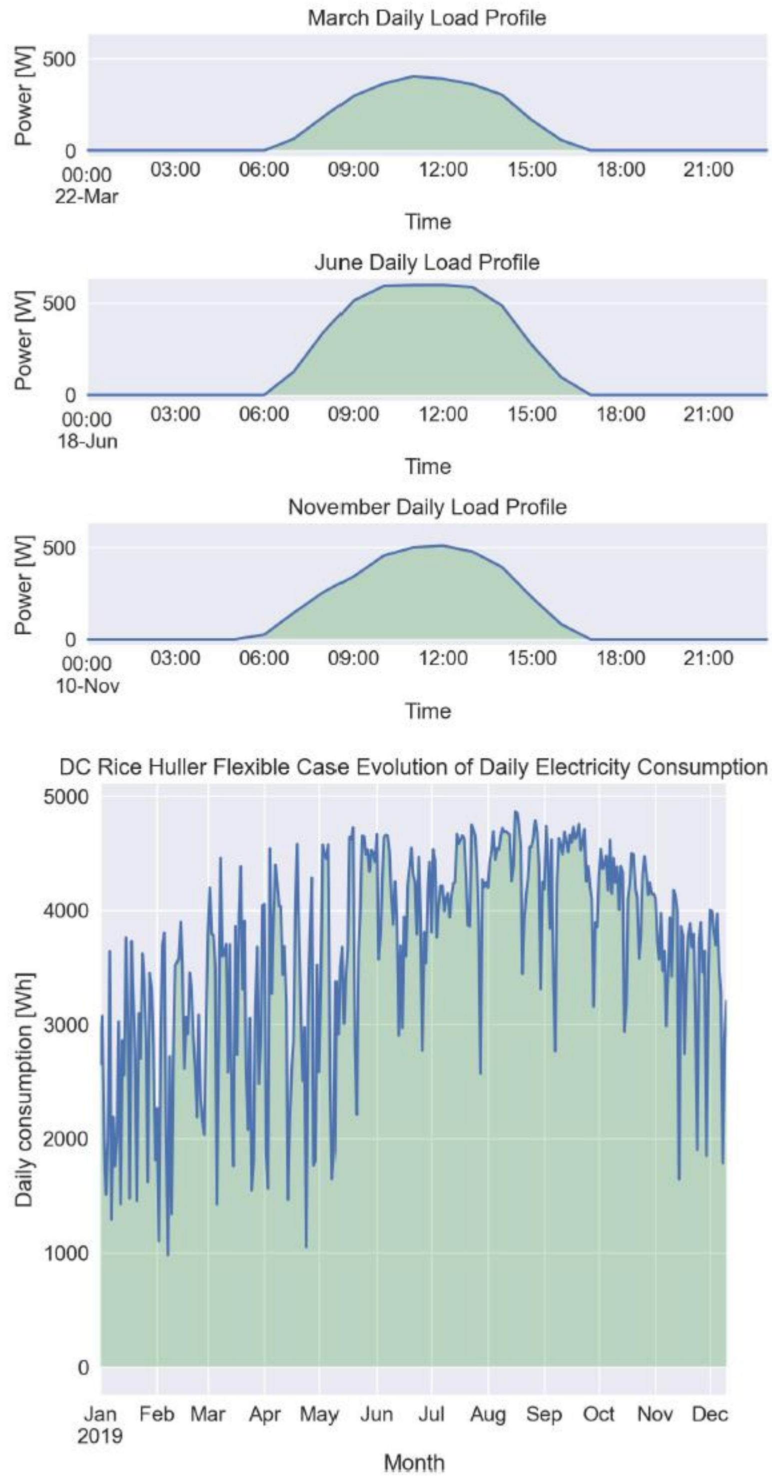


Figure 17: DC Rice Huller Flexible Case - Typical Load Profiles

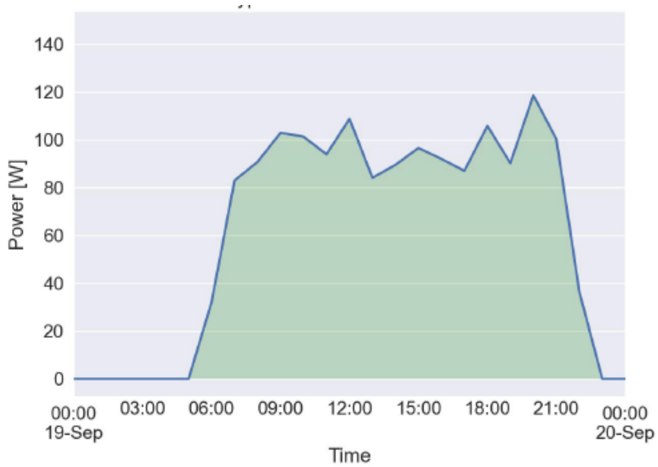


Figure 18: Typical Freezer Load Profiles

It must well be noted that the use of a rice huller – thereby the estimated load curve – is highly dependent on the availability of rice, and local setting. From the interviews conducted we can derive the operational patterns of the current productive activities using the diesel-based rice huller. The interviews suggest a strong seasonal variation in the use of the rice huller, ranging between 1 h to 2 hours of use per day in the rainy season up to 9 hours a day in June. Based on the monthly production of ice hullers assessed via survey of Nanoé, we interpolated the required rice to be processed in every respective hour of the year. We further assumed the operation of the rice huller to start at 6 am in the morning as suggested by one interviewee and finalize once the calculated output of the specific day has been reached (with three hours break between 11 am and 2 pm). Fitting the load curve in our hourly-based model, the rice huller would for example produce 84 kg paddy rice per hour between 6 am and 8 am in January, but 71 kg/h per hour between 6 am until 11 am and again from 2 pm until 6 pm in June. As this seasonal constraint may significantly influence the results, we neglect any operational freedom in the scenario “flexible operation”, in which we only constrain for a minimum required yearly output of rice. Notably, this scenario poses an unrealistic extreme. However, it reflects (extreme) adoption of the user behaviour to respect energy system constraints.

According to the current model of the nano grids, PV is the only RE source considered. PV irradiation data was obtained via *renewables.ninja* as a time series in hourly resolution. PV panel tilt was assumed to be optimal with -29° and reference city of Maputo meteorological station [5]. Losses including e.g., array mismatch, dirt, and shading were assumed to be 10 % [6].

Scenario Analysis

In this section, we analyse the distinct scenario models developed. To evaluate the scenarios and systems modelled, technical and economic measures of results are introduced. The economic measures include:

1. Total annualized costs (TAC): as stated in the objective function (see Annex 5) the TAC of the energy system including investment in assets and operational expenditures. We neglect any labour costs or other project and company specific costs.
2. Levelized costs of system (LCOS): the LCOS reflect the average costs per kWh of useful energy produced by the system to serve energy as

Equation 1:

$$LCOS = \frac{TAC}{Energy_{served}}$$

The terminus $Energy_{served}$ includes the total energy delivered, including residential loads and PUE loads.

3. Levelized costs of electricity for residential loads (LCOE $_{residential}$): We define the Levelized Costs of Electricity Residential as the average cost per kWh of useful electricity energy produced by the system to serve residential electric loads. Thereby, we divide the annualized costs of producing electricity (notably excluding any cost associated with the potential PUE loads) by the total electric load served.

Equation 2

$$LCOS = \frac{TAC}{Energy_{served}}$$

With c_{PUE} [USD/yr] as marginal costs of the system components required to serve the amount of energy for the PUE load, and E_{PUE} [kWh/yr], and El_{served} as total electric power served to residential electric loads[kWh/yr].

4. Levelized costs of electricity for service of the PUE (LCOE$_{service}$): Analogous to the LCOE $_{residential}$, we calculate the levelized costs of the PUE service as

Equation 3

$$LCOE_{Service} = \frac{TAC - c_{residential\ system} * El_{residential}}{E_{Service}}$$

With $c_{electricity\ system}$ [USD/yr] as marginal costs of the system components required to serve the residential electricity loads El_{served}, and $E_{Service}$ as the required energy delivered to satisfy the PUE load.

We must further detail the methodology applied to calculate the marginal costs of the PUE sub-system c_{PUE} and residential electricity supply sub-system $c_{residential\ system}$ respectively (analogous for $LCOE_{Service}$and $LCOE_{residential}$). In our analysis, we follow the approach of to take an objective technical perspective, considering the share of costs of installation and use of the total system from the bottom up. We therefore calculate the fraction of asset costs, e.g., PV investment costs, which are required to feed the PUE or residential electricity supply sub-systems respectively by relying on the share of PV electricity flows through each sub-system.

To evaluate the results on technical measures, we report the

1. Excess electricity share: fraction of electricity produced by PV divided by the electricity consumed by residential or PUE loads and lost during conversion (e.g., in the battery). Excess hours: total number of hours in which excess of electricity is produced.

Both technical measures of result can be seen as reflecting the technical energy efficiency of the energy system to match the production and demand of electricity.

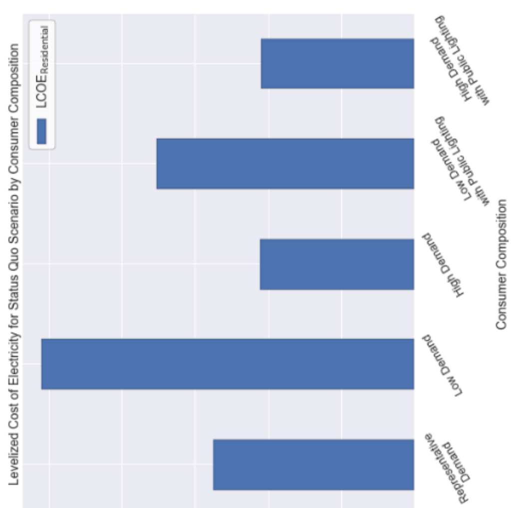
3.5. Modelling Results

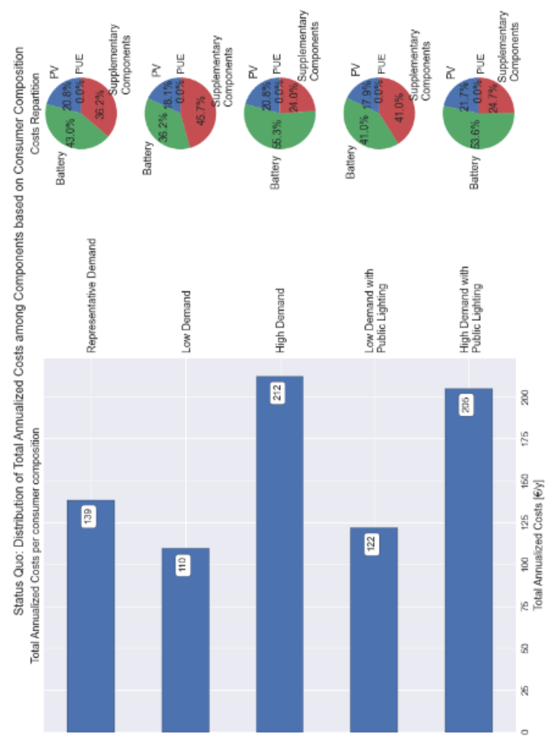
In the following, extracts of the results from the scenario modelling are depicted and evaluated. The following table (Table 6) contains an overview of economic evaluation measures as described in the previous section. An overview of the technical evaluation measures is included in the appendix (Annex 6).

3.5.1. Evaluation of Integration Scenarios

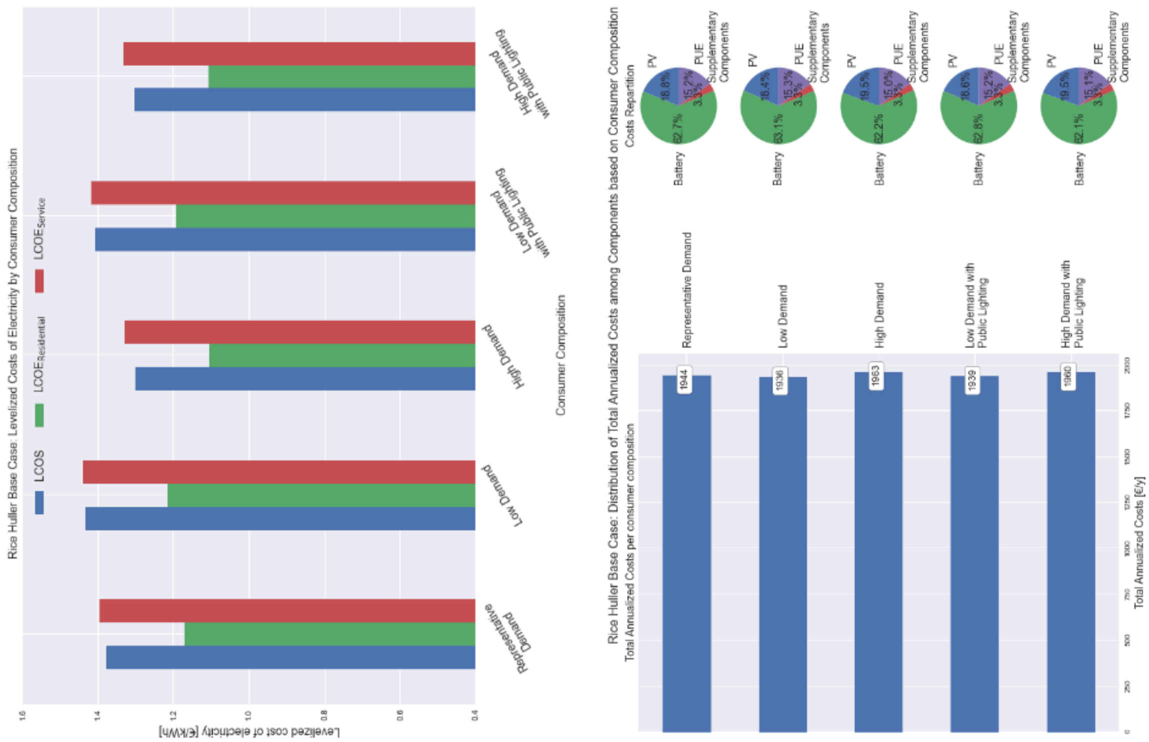
In Table 5, the economic evaluation measures of four scenarios are provided, namely (1) Base case nano grid, (2) Constrained integration of a rice huller in a nano grid, (3) flexible integration of a rice huller in a nano grid, and (4) integration of a freezer. For each integration scenario two separate graphs are provided, the first of which gives an overview of the LCOS and the LCOE where applicable and the second graph provides an overview of the total annualized investment cost and the respective share of cost of the individual system components. For all four integration scenarios, all previously defined consumption scenarios are computed (Representative Demand, Low Demand, High Demand, Low Demand with Public Lighting, High Demand with Public Lighting). Table 5 is followed by a discussion of the modelling results.

a)



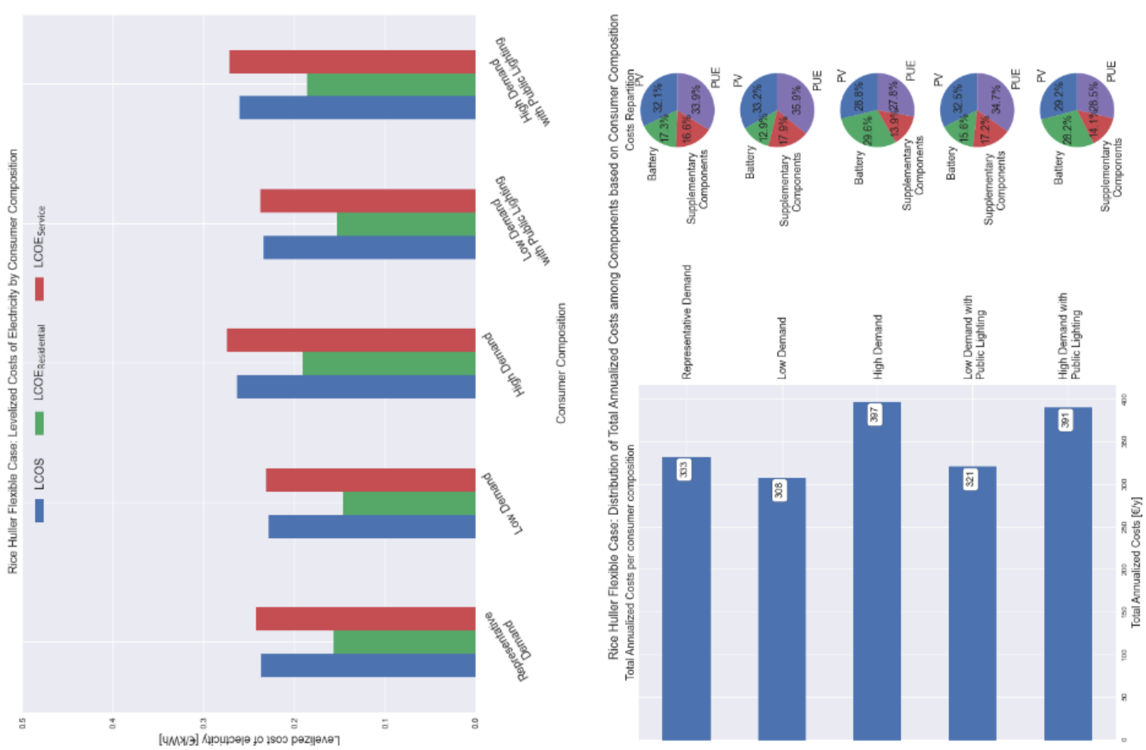


b)



Rice Huller Base Case: Levelized Costs of Electricity by Consumer Composition
LCOS
Consumer Composition
Levelized cost of electricity [€/kWh]
Rice Huller Base Case: Distribution of Total Annualized Costs among Components based on Consumer Composition
Total Annualized Costs per consumer composition
Costs Repartition
Total Annualized Costs [€/y]
Representative Demand
Low Demand
High Demand
Low Demand with Public Lighting
High Demand with Public Lighting
1944
1936
1983
1939
1960

c)



Rice Huller Flexible Case: Levelized Costs of Electricity by Consumer Composition
LCOS
Consumer Composition
Levelized cost of electricity [€/kWh]
Rice Huller Flexible Case: Distribution of Total Annualized Costs among Components based on Consumer Composition
Total Annualized Costs per consumer composition
Costs Repartition
Total Annualized Costs [€/y]
Representative Demand
Low Demand
High Demand
Low Demand with Public Lighting
High Demand with Public Lighting
333
308
397
321
391

d)

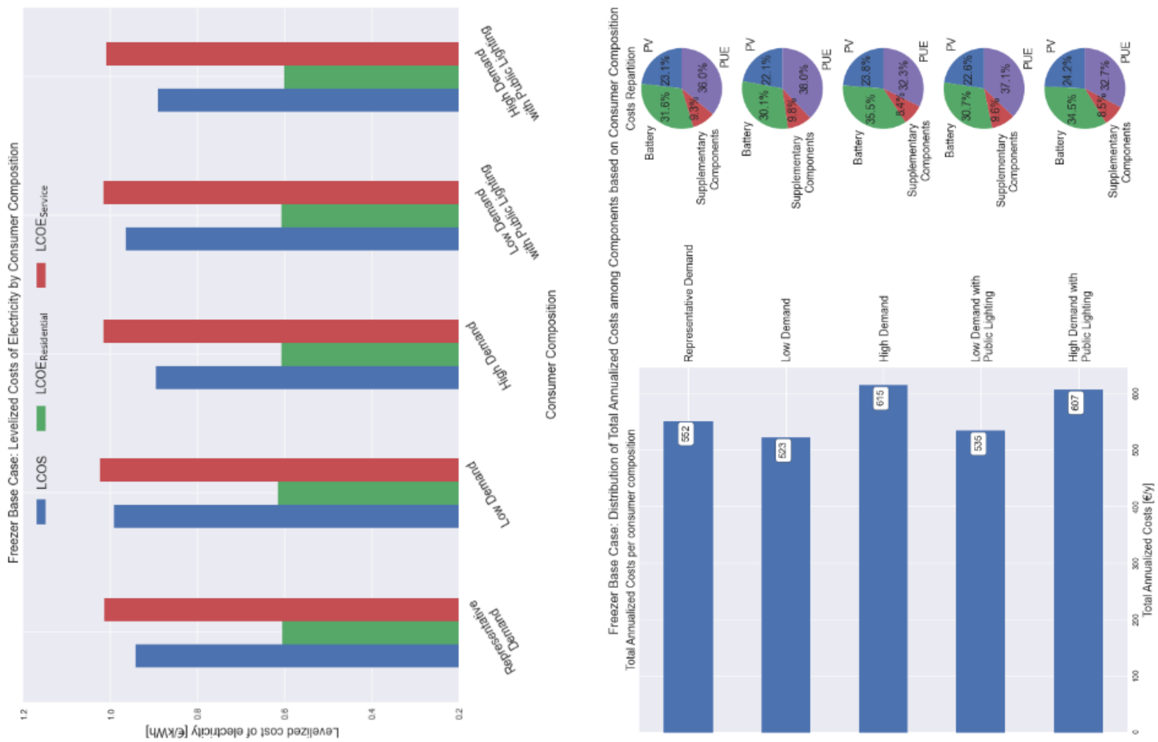


Figure 19: Overview of the economic evaluation measure for PUE integration scenarios
a) Economic evaluation measures: Base Case scenario
b) Economic evaluation measures: Integrated Rice Huller scenario
c) Economic evaluation measures: Flexible Ricer Huller scenario
d) Economic evaluation measures: Integrated Freezer scenario

a) **Base Case Nano grid.** For the Base Case Nano grid, the economic evaluation measures reveal that the High Demand consumption scenario exhibits the highest total annualized investment cost, and the Low Demand consumption scenario exhibits the lowest annualized investment cost. For the $LCOE_{residential}$ the results are inverted, with the Low Demand consumption scenario showcasing the lowest $LCOE_{residential}$ and the High Demand consumption scenario the lowest. The percentage share of the cost for the battery is noteworthy, as the consumption scenarios with overall higher demand profiles result in significant costs for the battery. This is a result of the distinctive evening peak associated with the high demand profile. The low solar irradiation in the evening, in combination with the high demand results in a need for large battery capacities. For the High Demand and the High Demand with Public Lighting the cost for the battery is more than half of the overall cost.

b) **Integrated Rice Huller.** When comparing the TAC of the Base Case Nano grid scenario with the case of a constrained integration of the rice huller, it becomes clear, that the PUE significantly impacts the TAC. While the percentage share of total cost of the rice huller is around 15% for all consumption scenarios, the overall system cost increase is substantial. The TAC in the Integrated Rice Huller Scenario with a Representative Consumption composition is 12 times larger than the TAC of the Base Case Nano grid scenario with the same consumption composition. In the Integrated Riche Huller scenario, the variance in TAC for the various consumption compositions is very small. The maximal variance is 1%. The differences in the $LCOS$ are a result primarily due to the varying degrees of excess electricity in the systems (see Annex 6). In the same way as in the Base Case Nano grid scenario, the smallest $LCOE_{residential}$ are exhibited by the Low Demand scenario. However, the variance in the $LCOE_{residential}$ among the consumption compositions is much smaller than in the Base Case Nanogrid scenario. In the Base Case Nanogrid scenario the $LCOE_{residential}$ in the High Demand consumption composition are 138% larger than the $LCOE_{residential}$ for the Low Demand consumption composition. In the Integrated Rice Huller scenario, the $LCOE_{residential}$ in the High Demand consumption composition are only approximately 10% larger than the $LCOE_{residential}$ for the Low Demand consumption composition. While there is a significant reduction in the cost of electricity provision for households between the two scenarios in the case Low Consumption composition, the $LCOE_{residential}$ increase for High Demand and High Demand with Public Lighting scenarios. It can further be noted, that for all consumption compositions, the $LCOE_{residential}$ is smaller than the $LCOE_{Service}$, which can be interpreted as a de facto subsidy for the electricity consumption of households.

c) **Flexible Rice Huller.** This case represents a scenario, in which a large degree of flexibility is in the operation is possible. The overall amount of rice processes is the same however, the processing of the rice can occur over the span of the entire year. The underlying assumption is a rice storage that is integrated in the system and allows a flexible operation.
While there is no significant variance between the TAC of the different consumption compositions for the Integrated Ricer Huller scenario, the TAC for the High Demand consumption composition is 28% higher than the TAC in the Low Demand consumption composition in the Flexible Rice Huller scenario. In addition, the TAC for all consumption compositions is of a different magnitude in the Flexible Rice Huller, when compared to the TAC for the different consumption composition

of the Integrated Rice Huller scenario. The difference is most significant for the Low Demand consumption composition with a reduction in the TAC of approximately 84%. With a $LCOE_{residential}$ in the Base Case Nanogrid for a Low Demand consumption composition of approximately 2,5 EUR/kWh and a $LCOE_{residential}$ in the Flexible Ricer Huller for the same consumption composition of approximately 0,15 EUR/kWh, the $LCOE_{residential}$ is reduced by 94%. The same comparison with an underlying High Demand consumption composition showcases a reduction in $LCOE_{residential}$ of 82%. In the Flexible Rice Huller scenario, the High Demand consumption composition exhibits the highest $LCOE_{residential}$ and the Low Demand consumption composition exhibits the lowest $LCOE_{residential}$. This is contrary to the Base Case Nanogrid scenario. Furthermore, it should be noted that the percentage share of the battery cost is significantly smaller than in the other considered scenarios, which is a result of the greater degree of flexibility. For the Low Demand consumption, the battery cost represents merely 12,9% of the TAC.

d) **Integrated Freezer.** For the evaluation of the results of the Integrated Freezer Scenario, the results are compared to the Base Case Nano grid scenario. With the introduction of the PUE, the TAC increases. For the High Demand consumption composition, the TAC is increases by 190% and for the case of the Low Demand scenario the TAC increases by 175%. There is only a small variance in the $LCOE_{residential}$, suggesting that the applicable consumption composition has little impact on the cost of electricity provision for households. The comparatively high percentage share of the cost of the PUE is noteworthy with a share of up to 37.1% in the Low Demand with Public Lighting case. The comparison of the Base Case Nano grid and the Integrated Freezer scenarios reveals that through the integration of the freezer the $LCOE_{residential}$ can be reduced substantially. For the Low Demand consumption composition, the $LCOE_{residential}$ are reduced by 75% and for the High Demand consumption composition the $LCOE_{residential}$ are reduced by 43%.

3.5.2. Aggregated Modelling Results

Important learning can be derived by comparing the modelling results for different types of PUE integration and by comparing the modelling results of the two selected PUE. The modelling results showcase the importance of the mode of operation. The TAC, as well as the levelized economic indicators underline the wide variance in potential outcomes and underline the necessity and importance of maximizing the system flexibility. While neither the Integrated Rice Huller scenario nor the Flexible Rice Huller scenario is likely to reflect the reality exactly, the analysis identified the range of potential economic outcomes and underlines the fact that more flexibility in the operational environment allows for a more cost-efficient energy system design. The large variance in the TAC is not only significant because it the higher system costs are passed on to the users of the system, but also because a high investment cost can be a major barrier to implementation. The direct comparison of the Integrated Rice Huller scenario and the Flexible Ricer Huller scenario also reveals that the mode of operation and therefore the degree of flexibility assumed during the system design, has an influence on the most suitable consumer composition with which the PUE is paired. Regarding the cost of providing electricity to households it is important to note, that in the case of a constrained integration of the rice huller only for some consumer compositions the $LCOE_{residential}$ was reduced through the integration of the PUE. In contrast, for both the Flexible

Rice Huller scenario and the Integrated Freezer scenario there was a significant decrease in $LCOE_{residential}$ for all consumer compositions, when compared to the scenario without a PUE integrated.

The case study analysis reveals that the one key factor in the successful implementation of PUE is the flexibility of operation the selected PUE allows. In the case of the integration of a rice huller under the assumptions the TAC increases by almost factor seven in for the low demand consumption profile of users, when comparing a highly constrained integration scenario (Integrated Rice Huller scenario) and a highly flexible (Flexible Rice Huller scenario). The fundamental importance of flexibility allowed by the PUE suggests that further investigation regarding the type of PUE and the mode of integration should include PUE that allow for an integration of a storage. The authors propose to include water pumping systems in future investigations, as an integration of a storage for a water pumping system is technologically easy to implement and does not entail significant extra investment cost.

When taking the relation between socio-economic characteristics and the consumption patterns into account additional learning can be derived from the modelling results. In a scenario, in which the operation of the rice huller is constrained, the integration of the PUE is more cost-efficient in energy systems with many consumers that fall in Cluster 0 and therefore are subscribed to a higher-tier tariff, such as the Multimedia-tariff and own multiple light bulbs and more energy-intensive appliances.

3.5.3. Considerations For the Local Value Chain

The case study has focused on the explicit bilateral relation between the community structure with associated energy consumption patterns and the integration of PUE. However, the integration of PUE in energy systems, communities and energy access projects is complex, given the multidimensional and bilateral relation of the PUE with the ecosystem embedded in. Previous research has developed the causal relation of PUE integration in energy access projects, identifying risks, preconditions and external factors impacting the implementation of PUE in projects [7] show the complex causal loops associated to energy access, and productive activities [Riva et al.]. While the transfer and implementation of the recommendations of these complex studies is out of scope of this case study analysis, we provide insights gained from semi-structured interviews carried out during the site-visit to point out to selected sensitive aspects in the local value change, likely to be influenced when integrating PUE.

Reflecting on the status-quo of the productive activities, Figure 20 a) and b) illustrate the changes in the local value chain when introducing the electric productive uses of the rice huller and freezer, respectively.

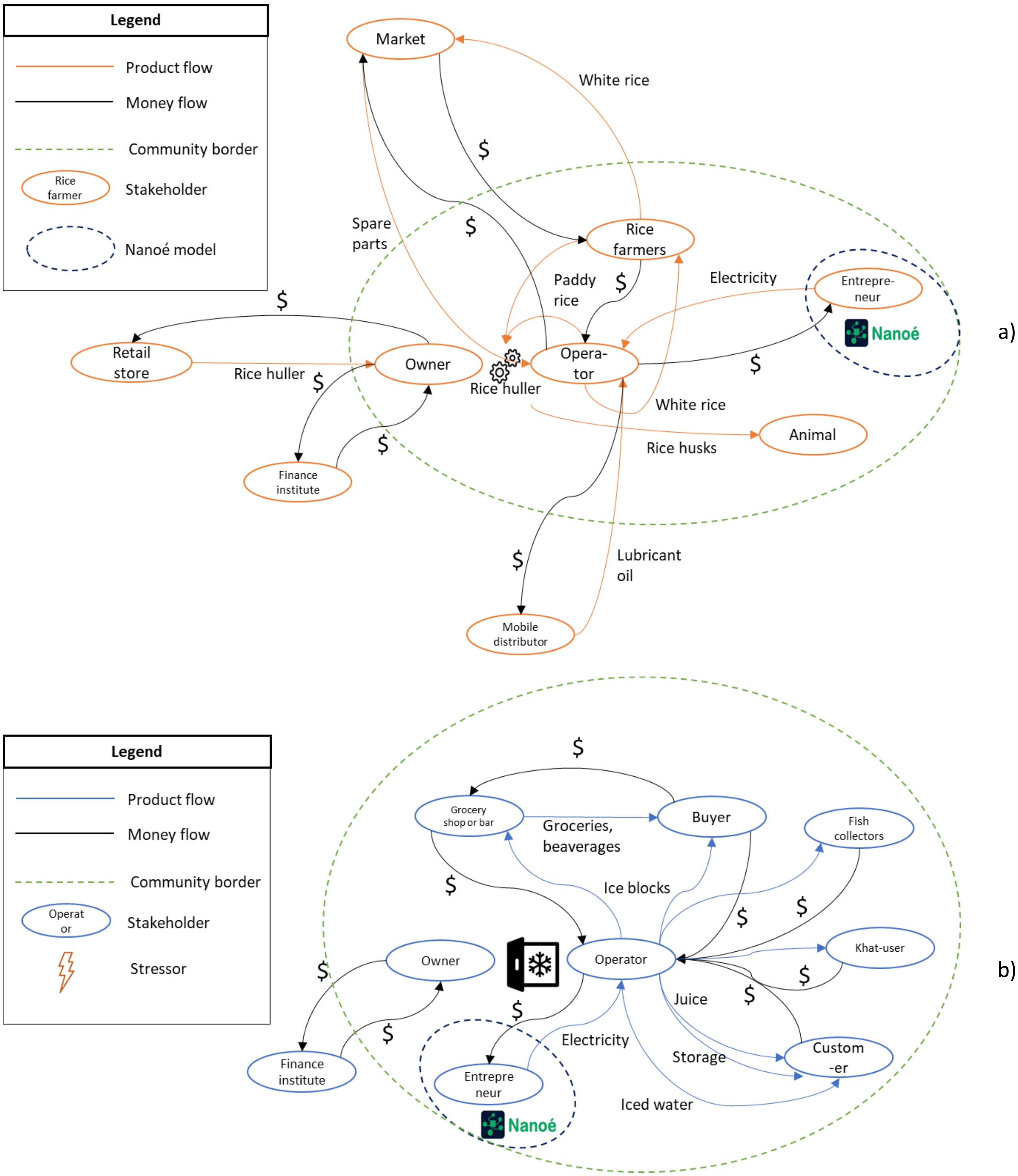


Figure 20: Product flow and value chain associated to the integration of the electric PUE; a) DC rice huller and b) DC freezer

In both cases it is striking that the dependency of the community on external deliveries, i.e., diesel fuel and ice blocks, will be reduced. As such dependencies clearly pose a stressor to the business, and eventually customers of the business, positive impact may be expected. However, as a turnover, while increasing the resilience of the specific community, the intermediate stakeholder delivering the goods to the community may even loose income opportunities. It must therefore be considered within PUE projects that the entire value chain may be impacted, and it is not given per se that everybody may profit from increased uptake of PUE. Awareness raising amongst stakeholders across the entire value chain is essential to prevent from causing inequalities.

Our analysis included the costs of the PUE within the energy system costs. This objective point of view showed that in even the most conservative constellation of PUE and community energy consumption, the share of costs of the PUE asset alone account for maximum of a third of the total energy system costs. However, for individuals, the costs of PUE assets may pose a significant barrier to the uptake. In the case of a DC freezer, one interviewee, whose family owns a DC freezer reports from the burden of a microcredit running for two years with monthly paybacks of 160,000 AR (ca. 33€). In addition, the electricity consumed by the freezer is charged via a dedicated tariff, causing a bill of approximately 38,000 AR per week (ca. 8€). However, the owner reports from daily profits of 5000 AR (ca. 1€) from selling a wide spectrum of goods, especially iced water for Khat users, juice in glasses, or selling ice for other local grocery store which require ice for cooling food and beverages (notably these are the products desired to sell from the interviewee in section 2 when improving the cooling ability). While the economic benefits for the PUE owner thus are evident, our analysis shows potential for other community members to gain economic benefits from the integration of PUEs, when assuming different stacked tariffs in place. We observed the difference in $LCOE_{residential}$and $LCOE_{Service}$, during the analysis. Notably, the LCOE only reflect a part of the costs to be included when determining a tariff but may be seen as indicative for the tariff to set. From our analysis, we can observe that the $LCOE_{residential}$ (significantly) decreases when integrating the PUE, while the $LCOE_{Service}$, exceed the $LCOE_{residential}$. To illustrate the consequences, we conduct a very simplified thought experiment. Considering a “low-demand” residential constellation, the average annual electricity consumption per household is 10.6 kWh. When adopting the $LCOE_{residential}$as a tariff, in a base case nanogrid ($LCOE_{residential}$= 2.5€/kWh) the annual costs of electricity per household would be approximately 27€. We now consider the case of having four “low-demand” clients, and one freezer integrated into the system, who is charged a tariff in the level of the $LCOE_{Service}$,. Adopting the new $LCOE_{residential}$found within the analysis for integrating a freezer ($LCOE_{residential}$= ca. 0.6€/kWh), the annual costs of electricity to pay for each household are reduced by a fourth to approximately 6.5 €, while the costs for operating the freezer would total to 533€ per year. While this calculation is a very simplified approach, it clearly shows the distributional monetary benefits amongst the community potentially to be unlocked when setting an appropriate tariff scheme. Thus, our analysis supports the suggestion from literature [15] that the entire local economy may be improved when overcoming initial barriers of investment into the PUE to be integrated into the system.

Beyond the direct local impact, the DC electric PUE contribute to achieving overarching pressing climate change mitigation goals. Based on a simplified calculation we may estimate the direct local CO_2 emissions saved when substituting a diesel-based rice huller (emission factor approximately 265 gCO_2/kWh) to 1269 $kgCO_2$ per year. Even more striking, the emissions saved from producing the amount of ice required for one year of operating the bar business described in section 2 via renewable resources instead the current production in diesel powered ice factories could amount to 2500 $kgCO_2$ – 3000 $kgCO_2$ per year – while even neglecting the emissions caused from transportation (calculation is simplified and based on the product sheet of an ice factory.

4. EVALUATION AND RECOMMENDATIONS

The investigation conducted in the case study analysis is limited to data from one village in the ENERGICA project's demonstrator region. However, this deliverable goes beyond the case study's scope by conducting generalized and predictive interpretations to provide insights into the potential impacts of PUE integration on a larger scale. These interpretations are based on previous project outputs and section 1 information. The report stresses the significance of productive uses of energy in promoting sustainable development and improving livelihoods in Africa. It highlights the need for a comprehensive approach that considers not only energy access but also the specific needs and contexts of communities. Additionally, the report emphasizes the potential for productive uses of energy to generate income and create economic opportunities and promote circular economies.

According to [16] the most effective way to improve financial outcomes through productive uses is to increase the load factor with productive uses of electricity that operate year-round. [15] Reviewed the outcomes and impacts of small-scale energy projects in the global south and found out that to enable productive activities to flourish on a broader level, it is necessary to include activities, resources, and information that support the productive use of energy, such as training, equipment, and market research, as an integral component of the energy project itself.

Integrating PUE into community-level energy systems can be an effective way to increase access to electricity, support economic growth, and reduce inequalities in rural areas [17]. However, to design effective energy systems, it is crucial to understand how socio-economic characteristics and PUE consumption patterns interact. As outlined in section 1.1 engaging with the existing local structure of stakeholders, promoting inclusive policies, and capacity-building programs are essential for the success and sustainability of community-level energy systems. Additionally, it is important to consider cultural values, community engagement, and economic development in designing energy systems that meet the needs of all users.

Rice hauling services are important components of the agricultural value chain in the Diana region. The impact of productive uses of energy for rice hauling on the economic well-being of a community is significant and multifaceted. Firstly, access to energy for rice hauling can increase efficiency and reduce losses. In the absence of electricity, rice pre- and post- harvest handling can be slow, labour-intensive, and prone to losses due to exposure to weather and pests. Access to energy for rice hauling can reduce losses and increase efficiency, thereby increasing the income of farmers and reducing post-harvest losses. Secondly, productive uses of energy can facilitate the growth of small and medium-sized enterprises (SMEs) that provide rice hauling and drying services. Access to reliable and affordable energy can enable the establishment and growth of businesses that provide these services, creating employment opportunities and contributing to the growth of local economies. Thirdly, access to energy for rice hauling and drying services can improve the quality of rice, making it more attractive to buyers and commanding higher prices. The use of energy-efficient technologies can reduce the moisture content of rice, thereby reducing the risk of spoilage and improving the quality of the produce. This can lead to increased income for farmers and contribute to overall economic growth.

The case studies in section 3 revealed that the economic performance of a PUE system is significantly impacted by the way it is designed and operated. Two scenarios were compared - one with an Integrated Rice Huller and another with a Flexible Rice Huller, which showed that the mode of operation and the degree of flexibility assumed during the system design can influence the most suitable consumer composition for the energy system. Maximizing the flexibility of a PUE system can lead to more cost-efficient energy system designs, which can help reduce costs and improve economic outcomes. It is essential to consider the potential economic outcomes when designing PUE systems for productive uses and select the most appropriate consumer composition based on the mode of operation and degree of flexibility assumed during the system design. Having a flexible PUE system can cater to not only rice hauling needs, but also other farm produce described in section 1.1 when rice is not in season. By adhering to the times of day when farmers use the rice haulier the energy can be utilized for other areas of energy needed for the household. Furthermore, the wide variance in total cost is crucial because higher system costs can be passed on to users of the system, and high investment costs can be a barrier to implementing the system. Therefore, designing cost-efficient and flexible PUE systems is encouraged, which involves investigating the economic indicators of the location, commodity value chain structure, social construction, and energy needs of the community. By integrating these factors into the PUE, more tailored and effective energy solutions can be created that will enhance the communities' economic and address secondary challenges that come with lack of access to affordable and reliable clean energy.

On the other hand, fishing is also an important economic activity for the community as was indicated in D2.1 and mentioned in in section 1.1 PUE for freezing services for fish and ice makers can have a significant impact on the community's economic status. Access to energy for fish freezing services and ice-making can increase efficiency and reduce losses. The use of energy-efficient freezers and ice-making machines can reduce the pressure on the fishermen on the requirement for the fish to reach markets before spoilage, thereby reducing losses and increasing income for fishers and traders (2.4.1). This can contribute to the growth of local economies and poverty reduction. Along the fishing value chain, PUE can promote the establishment of local businesses that provide value-additional services which will create employment and contribute to the growth of local economies. PUE services can enable the expansion of fishing activities and the exploration of new markets. The use of energy-efficient freezing technologies can allow fishers to store their catch for longer periods, thereby enabling them to expand their fishing activities and explore new markets.

The information provided can be utilized to guide the actions carried out in Work Package 4 of the ENERGICA project.

PUE can promote a circular economy in rice farming and fishing communities by reducing waste, creating value from by-products, and promoting resource efficiency. PUE systems can effectively recycle rice waste, particularly husks, into valuable products. Rice husks are often disposed of as waste and can cause environmental challenges if not managed properly. However, energy plays a crucial role in transforming these husks into useful resources. One way to recycle rice waste is by using the husks as feedstock to generate clean energy. Rice husks can be combusted to produce steam, which is used to generate electricity in biomass power plants. This process can reduce the amount of waste that would otherwise be disposed of in landfills. Another way to recycle rice waste is by converting rice husks into biochar, a valuable soil amendment that can improve crop yields and soil fertility. Energy is used to convert the husks into biochar, which not only reduces waste but also improves the productivity and sustainability of farming practices. In addition, rice husks can be used to produce biogas through anaerobic digestion. Biogas can be used for cooking, lighting, heating, and electricity generation, thus providing a source of clean energy, especially for household consumption while reducing waste. Rice husks can also be used to make rice cake, a nutritious feed for livestock. This by-product of the rice milling process is a mixture of rice bran and rice polish, which can be compressed into cakes using a rice cake machine. Rice cake is a cost-effective way to recycle rice waste and can provide an additional source of income for farmers while reducing their dependence on expensive commercial feeds. All these possibilities can reduce waste and improve the sustainability of their farming practice while generating additional income and reducing unemployment rates.

PUE integration into the fishing industry in the communities of Diana, will not only promote fish shelf life but also can be an attractive solution for providing value addition to the fish waste. One potential application of energy is in the processing of scales into high-value products such as fishmeal for animals and chicken feed or fertilizer. Processing fish scales requires energy-intensive equipment such as grinders and dryers that can be costly to acquire and expensive to run. Therefore, access to reliable and affordable energy through a PUE model is essential for the efficient and cost-effective processing of fish scales. use of fish scales in the value addition chain can bring multiple benefits, including additional income generation, waste reduction, environmental preservation, promotion of entrepreneurship and innovation, and creation of employment opportunities. The insights gathered can be applied to the development of activities for Task 7.3 in Work Package 7 of the ENERGICA project, which focuses on the feasibility of adding value to co-products in agriculture.

In addition to creating value from by-products, PUE can also promote resource efficiency by powering irrigation systems that reduce water waste and increase crop yields. Furthermore, PUE can reduce reliance on fossil fuels, which can help to mitigate the environmental impacts of energy consumption.

There are notably high potential positive impacts of PUE projects in reducing the dependency of communities on external deliveries, such as diesel fuel and ice blocks. However, there are also negative impacts from PUE on the local economy. A reduction in dependency can increase the resilience of the community as they become less reliant on external resources that may be subject to supply chain disruptions or price fluctuations. It is important to consider the potential impacts on the entire value chain, as increased uptake of PUE may lead to a loss of income opportunities for intermediate stakeholders delivering goods to the community and entrepreneurs. This highlights the need for awareness raising amongst stakeholders across the entire value chain to prevent the potential for inequalities and rigidity in the uptake of RET solutions. For example, in the case of Diana's demonstrator solution, the PUE project will provide the community with access to rice-hauling solutions, freezing services, and the possibility of solar-powered irrigation pumps in the future. Access to clean water was a need identified in D2.1. This will reduce their reliance on expensive diesel pumps, diesel-powered rice hauliers, and outsourcing for cooling and freezing services, increasing their resilience, and reducing their costs. However, the project may also impact the income of local vendors who previously sold diesel fuel for the pumps, provided rice hauling and transportation services, and provided preservative services for fish and its transportation to the market.

To effectively address the potential negative impacts of PUE adoption and promotion, a comprehensive and participatory approach involving all stakeholders in the value chain is necessary. By doing so, it becomes possible to develop interventions that mitigate potential negative impacts and promote fair outcomes for all stakeholders. Several strategies can be implemented to achieve this, such as conducting a thorough stakeholder analysis, identifying potential risks, and designing interventions to address negative impacts. In addition, engaging all stakeholders in the value chain is crucial to ensuring that the project benefits everyone and creates a win-win situation. Investing in capacity-building programmes [18] and creating awareness campaigns to inform stakeholders about the benefits of PUE and potential negative impacts can help mitigate negative impacts. Participatory monitoring and evaluating the impacts of PUE adoption and promotion over time can identify any unintended consequences and ensure that interventions are adapted accordingly [19]. Finally, developing appropriate policies and regulations that encourage PUE adoption while protecting the interests of all stakeholders is essential. By employing these strategies, a comprehensive and inclusive approach can be taken to minimise negative impacts and promote equitable outcomes for all stakeholders.

To ensure that interventions are adapted accordingly, it is important to have a clear understanding of the needs and perspectives of all stakeholders involved [20]. This can be achieved through ongoing consultation and engagement with affected communities, as well as through the use of data and evidence-based research. Additionally, it is important to consider the potential unintended consequences of any interventions and develop strategies for mitigating these risks. In terms of promoting PUE adoption, there are several policies and regulations that can be put in place to encourage uptake while also protecting the interests of all stakeholders. These might include financial incentives for households or businesses that adopt PUE measures, as well as regulations around energy efficiency standards for PUE infrastructure or appliances. Ultimately, taking a comprehensive and inclusive approach to PUE adoption is essential for promoting equitable outcomes for all stakeholders. This means considering not only the environmental benefits of PUE measures but also their social and economic impacts.

It is impossible to disregard obstacles that can hinder the effective implementation of productive energy usage, such as insufficient financing, inadequate infrastructure, and limited technical expertise [20]. Tackling these challenges, will need a wide array of solutions including, the establishment of regulatory and policy frameworks that facilitate the integration of productive energy usage, the deployment of innovative financing mechanisms, capacity-building initiatives for local stakeholders, and fostering of partnerships between multiple actors. Working with the local stakeholders already mapped in D2.2. can further foster the uptake and upscaling of the PUE model by the communities. Utilising their knowledge and experience will boost chances for sustainability.

Future investigations in this context should focus on PUE technologies that allow for storage integration and water pumping systems. Overall, this study highlights the potential benefits of PUE technologies in reducing the cost of providing electricity to households and suggests that flexibility in the mode of integration is crucial to realizing these benefits.

To gain a comprehensive understanding of the intricacies involved in incorporating PUE systems within community-level energy systems and devise efficient solutions, additional research and experimentation are essential. Adopting a holistic and integrated approach to community-level energy system planning, while ensuring the fulfilment of sustainable development objectives like poverty reduction, gender equality, and environmental sustainability, can be accomplished by catering to the distinct requirements of each community. Based on these findings, the report suggests the implementation of several strategies, such as conducting diverse case studies, exploring innovative technologies, facilitating participatory decision-making, and evaluating the impact of sustainable development goals.

Overall, this report provides valuable insights into the potential benefits and challenges of integrating productive uses of energy into energy systems in Africa. It provides proposals that can be adopted to advance sustainable development through improved energy access and eco-friendly transitions, all while maximizing sustainability and the potential for broader scale implementation. The report highlights the relevance of PUE in addressing the need for rice hauling and cooling and freezing services in the Diana region. However, further research is recommended to explore other PUE options that could address the daily needs of the communities while taking into consideration their social and economic challenges. It is important to ensure that the implementation of PUE projects does not negatively alter their social and cultural structures. Therefore, a careful approach is necessary to ensure that PUE interventions are aligned with the community's values and priorities, while also addressing their energy needs and promoting socio-economic development.

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VII. ANNEXES

Annexe 1: Multi-Class Classification Problem

In machine learning, a classification problem consists in predicting the class of a variable using available data. The aim is to obtain the best outcome variable prediction from the available data. When a classification problem involves more than two classes, the problem is characterised as a « multi-class problem ». An algorithm calculates the probability for one unit to belonging to a class, and a classification rule assigns a specific class to the unit, usually the one with the highest probability. For two-class problems, a threshold can be defined to decide which class should be predicted. For multi-class problems several solutions exist [8].

To evaluate classification models and select the most appropriate one, or to identify the best parameter setting, a model performance indicator is needed. Classification metrics allow an assessment of the model's performance. Most of the metrics rely on the Confusion Matrix, which is a matrix that contains all the information about the decisions of the algorithm and the classification rule performance [8].

The confusion matrix shows the number of correct and incorrect predictions made by the classification model compared to the actual outcomes for a selected test set. It is typically represented as a square matrix with rows and columns representing respectively the actual and the predicted classes. The cells in the matrix stand for the count of instances of each combination of predicted and actual classes. For two-class problems, the four cells in the confusion matrix correspond to four possible outcomes:

- True Positive (TP): the cases where the model predicted the positive class correctly.
- False Positive (FP): the cases where the model predicted the positive class, but it was actually negative.
- False Negative (FN): the cases where the model predicted the negative class, but it was actually positive.
- True Negative (TN): the cases where the model predicted the negative class correctly.

An example of two-class problem confusion matrix is represented in Figure 21: Two-class problem confusion matrix with the row depicting the actual classes and the columns the predicted classes:

		PREDICTED		
	Classes	Positive (1)	Negative (0)	Total
ACTUAL	Positive (1)	TP = 20	FN = 5	25
	Negative (0)	FP = 10	TN = 15	25
	Total	30	20	**50**

Figure 21: Two-class problem confusion matrix

For multi-class problems, the confusion matrix row and columns would each contain all the classes listed in the same order, so that the elements correctly classified appear on the cells of the main diagonal. Figure 22 gives an example of a multi-class confusion matrix, where the correctly predicted element appears in green. The True Positives and the True Negatives are the correctly predicted elements, and thus they are the element contained in the confusion matrix’s main diagonal. The False Negative and the False Positives are the mis predicted elements and appear therefore outside of the matrix’s main diagonal [8].

		PREDICTED classification				
	Classes	a	b	c	d	Total
ACTUAL classification	a	6	0	1	2	9
	b	3	9	1	1	14
	c	1	0	10	2	13
	d	1	2	1	12	16
	Total	11	11	13	17	52

Figure 22: Mulit-class problem confusion matrix

Using the confusion matrix, several performance metrics can be derived, such as accuracy and balanced accuracy, precision, recall, and F1 score. These metrics provide valuable insights into the classification model' s strengths and weaknesses and help identify areas for improvement.

Accuracy is a classification metric that measures the proportion of correctly classified instances out of the total number of instances. It is calculated as the sum of true positive and true negative divided by the total number of instances:

Equation:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Accuracy provides an overall indication on how well a model is predicting outcomes across the entire dataset. The accuracy metric treats each individual instance in the dataset as having equal weight, meaning that each instance contributes equally to the overall accuracy score. Strong differences in class distributions can create imbalances in the prediction since a high populated class will have more weight than a lower populated one [8].

According to [8], accuracy is more appropriate when the focus is on individual instances rather than multiple classes. It means that if our interests are only focused on maximizing the number of correctly classified individuals, regardless of the distribution of classes and other performance indicators, then accuracy is the right metric.

Balanced accuracy provides a better evaluation of the classifier' s performance in imbalanced datasets, where accuracy may not be a good measure. It provides a more comprehensive view of the classifier' s performance across all classes, which can help identify potential issues and guide improvements. The balanced accuracy considers the number of individuals per class, allowing to equalize the influence of each class on the overall classifier performance. The following equations describes how to calculate this metric [8].

Equation:

$$Balanced\ Accuracy = \frac{\frac{TP}{Total_{row_1}} + \frac{TN}{Total_{row_2}}}{2}$$

Equation:

$$Balanced\ Accuracy\ Weighted = \frac{\sum_{k=1}^{K} \frac{TP_k}{Total_{row_k} \cdot w_k}}{K \cdot W}$$

When a dataset has a balanced class distribution, meaning that each class has roughly the same number of instances, both accuracy and balanced accuracy metrics tend to converge to similar values. However, when the class distribution is imbalanced, balanced accuracy provides a more reliable evaluation of the classifier' s performance, as it gives greater importance to instances from minority classes. In contrast, accuracy treats all instances equally and can sometimes favour the majority class, which may be beneficial if the primary goal is to achieve accurate predictions across the entire dataset but can be a disadvantage if the focus is on accurately predicting under-represented classes [8].

Application to our dataset:

By iteration on the multiclass prediction algorithm by varying power and energy quantiles, we computed the scores of the accuracy and the balanced accuracy metrics. Figure 23 a) and Figure 23 b) show the scores obtained by the metrics according to the quantile values. The best score returned by both metrics is respectively a score of 65.4% for accuracy, and 65.3% for the balanced accuracy metric. In both cases the best score corresponds to a quantile for energy of 0.5 and a quantile for power of 0.95. The fact that both metrics give scores close to the nearest tenth means that the imbalance in the representativeness of the classes in the population does not impact the algorithm with strong classification errors among the poorly represented classes.

The quantiles values associated with the highest score define an average proportion of occurrences where the household’s daily consumption exceeds the tariff thresholds. For the energy quantile it corresponds to 50% of the occurrences, for the power quantile it accounts for 5% of the occurrences.

a) b)

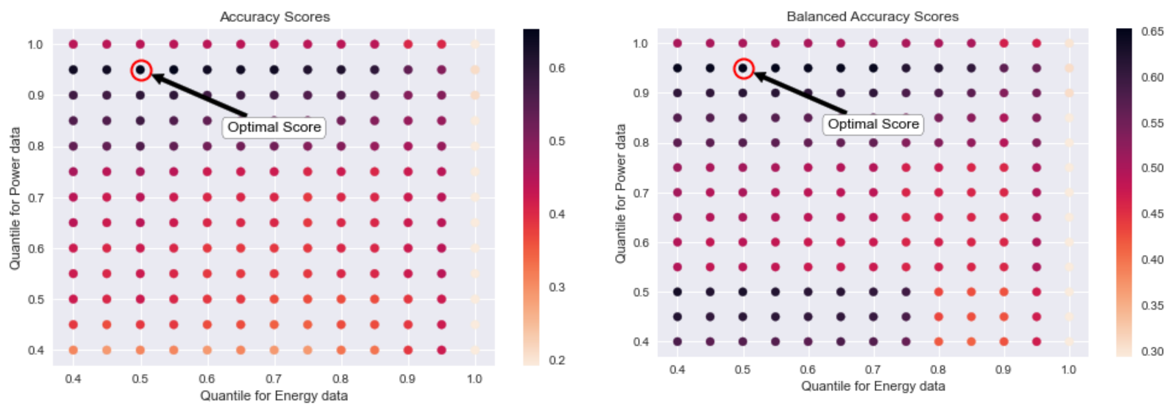


Figure 23: Computed scores of the accuracy and the balanced accuracy metrics

The corresponding confusion matrix is presented on Figure 24 The rows correspond to the actual classification, and the columns to the predicted classification. The main diagonal represents the number of correctly predicted consumers. The values below the diagonal correspond to a prediction error. However, this error is not necessarily due to the algorithm. The classification of a consumer in a tariff group lower than the real tariff can result from the consumer´s own behaviour. Indeed, if a consumer consumes less than to what his respective tariff allows, the algorithm will classify him in the most appropriate lower tariff group. Thus, in the context of this classification problem, we must consider that a household having subscribed to a given tariff will consume power or energy accordingly to the tariff’s definition. Another way to formulate this assumption is that the household could not subscribe to a lower tariff given its consumption. However, the values above the diagonal correspond to a real prediction error because it is an overconsumption of a household at a given tariff, which is precisely what the algorithm is supposed to take into account in his prediction.

We note that the tariff classes "Eco" and "Congel" are entirely correctly predicted. The "Multimedia" class is under-represented, and the unique individual of that class is incorrectly predicted. The remaining classes were predicted correctly for 60 to 70 percent of the individuals.

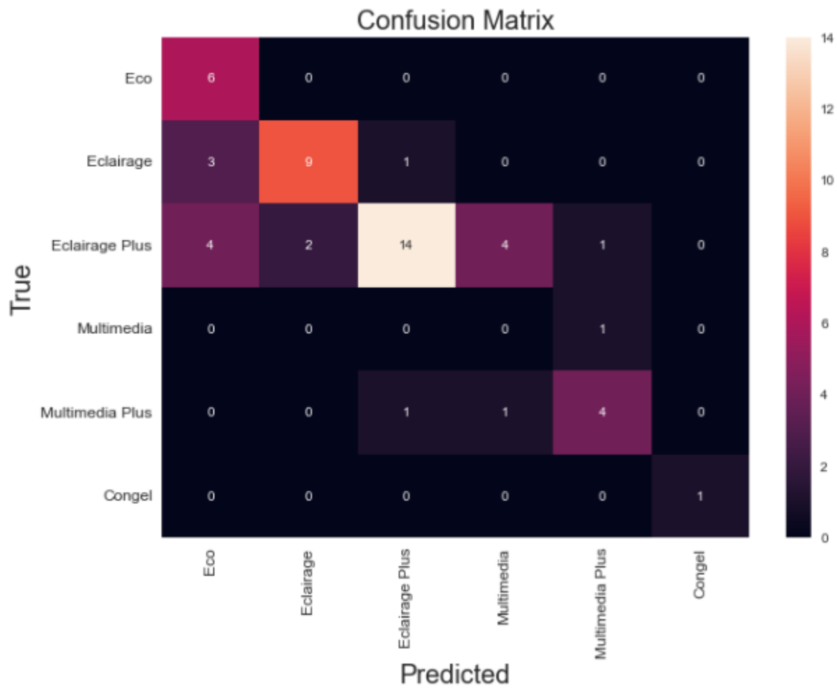


Figure 24: Confusion matrix of the associated Muli-class classification problem

Annexe 2: Descriptive Statistical Analysis

Table A1: Descriptive statistics of the sample group and Ambohimena village.

	Ambohimena		Sample Group	
	Total (n=209)	Share	Total (n=99)	Share
		Occupant status		
Owner	152	72,7	74	74,7
Tenant	13	6,2	5	5,1
Free	4	1,9	1	1,0
No answer	40	19,1	19	19,2
		Number of adults		
0	20	9,6	5	16,2
1	38	18,2	15	24,2
2	124	59,3	66	23,2
3	5	2,4	1	20,2

4	1	0,5	0	3,0
5	1	0,5	0	0,0
6	1	0,5	0	13,1
No answer	19	9,1	12	16,2
Average	1,7		1,7	
Median	2		2	
		Number of Children		
0	51	0,5	16	0,0
1	42	13,4	24	12,1
2	41	31,1	23	34,3
3	39	21,5	20	22,2
4	13	7,2	3	7,1
5	1	3,8	0	3,0
No answer	22	0,5	13	1,0
Average	1,6		1,7	
Median	2		2	
		Income [AR/m]		
50000	1	0,5	0	0,0
100000	28	13,4	12	12,1
150000	65	31,1	34	34,3
200000	45	21,5	22	22,2
300000	15	7,2	7	7,1
500000	8	3,8	3	3,0
a charge	1	0,5	1	1,0
No answer	46	22,0	20	20,2
Average	185802		183333,3333	
Median	150000	0	150000	
		Total costs estimation		
Average	70744		70753	
Median	60000		70000	
		Wall type		
Ravinala wood	79	37,8	40,0	40,4

Semi hard	42	20,1	18,0	18,2
Tin	2	1,0	2,0	2,0
Hard/stone	47	22,5	22,0	22,2
Wood	1	0,5	1,0	1,0
Other	0	0,0	0,0	0,0
No answer	38	18,2	16,0	16,2
		Roof type		
Leaves	20	9,6	9,0	9,1
Tin	147	70,3	72,0	72,7
Concrete	3	1,4	1,0	1,0
Other	1	0,5	1,0	1,0
No answer	38	18,2	16,0	16,2
		Floor type		
board	10	4,8	4,0	4,0
Concrete	157	75,1	76,0	76,8
Soil	0	0,0	0,0	0,0
Other	0	0,0	0,0	0,0
No answer	42	20,1	19,0	19,2
		Size		
small	19	9,1	7,0	7,1
large	56	26,8	21,0	21,2
medium	103	49,3	56,0	56,6
No answer	31	14,8	15,0	15,2

Annexe 3: Description of The Advanced Statistical Analysis Applied in The Investigation:

Annexe 3.1: K-Means Clustering.

Cluster analysis allows to group sample objects that have similar expressions in their characteristics. It is a machine learning algorithm used to partition a given dataset into a fixed number of clusters based on the similarity of the data points. This advanced statistical method is particularly effective to identify similarities between numerical data, allowing to define distinct groups of patterns... K-means clustering was chosen as the clustering method. K-means clustering does not require uniform cluster densities and allows for multiple dimensional data. The main shortcoming of the method compared to other kinds of cluster analysis is the challenge of pre-determining the appropriate number of clusters. However, this drawback can be overcome by calculating the silhouette score. The silhouette score s of each data point i, calculated according to Equation 1 quantifies the similarity of an object to its own cluster compared to a separate cluster. Ranging in a theoretical span between [−1, 1], a score closes to 1 indicates a high similarity and accordingly good performance of the clustering algorithm. Vice versa, a silhouette score of −1 indicates the opposite. The cluster number which holds the highest average silhouette score is optimal.

Equation:

$$s(i) = \frac{b(i) - a(i)}{max\,\{a(i), b(i)}$$

in which a = average intra-cluster distance, and b = average shortest distance to another cluster.

Annexe 3.2: Descriptive Statistics and Test Statistics

Descriptive statistics is a branch of statistics that aims to summarize and describe a dataset using basic statistical measures and visual representations. Depending on the type of variables included in the dataset under investigation, different statistical analyses are appropriate. Fundamentally, a distinction is made between continuous and categorical variables. When analysing continuous variables, descriptive statistics may include measures of central tendency such as the mean, median, and mode, as well as measures of dispersion such as the standard deviation, range, and interquartile range. When treating categorical variables, frequency tables and bar charts showing the number and percentage of observations in each category are appropriate.

To assess the statistical significance of the sample observations, a statistical test is applied. Statistical tests are used to determine whether a hypothesis about a population is likely to be true (with a defined likelihood) based on the sample data. Therefore, a null hypothesis is formulated, which implies that no significant difference between two or more variables under investigation exists. Subsequently, the statistical test uses the sample data to calculate a numerical value measuring the degree of difference between the sample data and the null hypothesis. The test statistic is finally compared to a critical value or p-value to determine whether to reject or fail to reject the null hypothesis. The p-value ([0;1]) is the probability that measures how likely the observed distribution difference is due to chance with 0 being very unlikely and 1 being very likely due to chance. Typically, a threshold value $P < 0.05$ is chosen to indicate a “significance” threshold, although this choice is arbitrary. The choice of test depends on the research question, the type of data being analysed, and the underlying assumptions of the statistical model.

Annexe 3.3: Chi-Square Test

The Chi-Square test is a non-parametric statistical test used to evaluate the association of two categorical variables. The Chi-Square test may be weaker than a parametric statistical test, but its results are more general due to less underlying assumptions on the dataset. The analysed variables are placed in a contingency matrix as follows: the first variable is arranged by row, while the second variable is arranged by column. The cells contain the count of individuals fitting in the respective intersected categories of both variables. The cell counts are compared to the expected counts, which are the theoretical individual counts if the distributions in each category of the predicted variable would be identical to the overall sample distribution. By summing the squared difference between observed and expected count over the expected count for each matrix cell, as displayed Equation 5 the Chi-Square value is calculated.

Equation:

$$\chi 2 = \sum \frac{(Observed - Expected)^2}{Expected}$$

To determine the significance level of the chi square statistic, the degrees of freedom of the matrix are calculated via Equation 6.

Equation:

$$(number\ of\ rows - 1) * (number\ of\ columns - 1)$$

The asymptotic significance is then computed on a statistical program using the calculated Chi-Square value and the Chi-Square table's degrees of freedom and compared to the critical value ($P < 0.05$) to eventually reject the null hypothesis. The conditions for applying a Chi-Square test are as follows:

1. The analysed variables should be categorical variables.
2. Variables categories are mutually exclusive: a subject fit into a unique category.
3. Each subject can only contribute data to one cell in the chi square table.
4. The study groups being compared must be independent of each other.
5. For the chi square test to be valid, the expected counts of each cell should be at least 5 in 80% of the cells, and no cell should have an expected count of less than 1.
6. The sample size must be sufficiently large to meet the expected frequency requirement, which typically means that the total sample size should be at least 5 times the number of cells in the Chi-Square table.

If conditions 5. or 6. are not met by the data, a Fisher exact test can be applied instead of a Chi-Square test.

Annexe 3.4: Fisher Exact Probability Test

The Fisher exact test is based on the hypergeometric distribution, which is a probability distribution that describes the number of successes in a fixed number of draws without replacement from a finite population. The hypergeometric distribution is used to calculate the probability of observing the observed contingency table under the null hypothesis of no association between the two categorical variables. Like the Chi-Square test, the Fisher exact probability test is used to determine if there is a statistically significant association between the two variables. For small samples and when Chi-Square assumptions on expected counts are not met, the Fisher exact probability test is a more accurate alternative.

Annexe 3.5: Chi-Square Test

While the Chi-square test investigates the significance of the relationship between two categorical variables, the strength of the relationship (effect size) must be calculated subsequently, e.g., via calculating Cramer´s V. The Cramer's V coefficient is a normalized version of the Chi-Squared statistic. It takes values between 0 and 1, with higher values indicating a stronger association. Generally, values around 0.1 indicate weak association, values around 0.3 indicate moderate association, and values around 0.5 or higher indicate strong association.

Equation:

$$Cramer\acute{}s\ V = \sqrt{\frac{\chi 2}{n * (r-1, c-1)}}$$

with $\chi 2$ as the chi-squared statistic for the contingency table of the two nominal variables, n as the total sample size, r as the number of rows and c as the number of columns in the contingency table, respectively.

Cramer´s V advantage over other measures of association is its independence of the sample size and the number of categories in the variables. However, Cramer´s V may not be sensitive enough to detect small differences in the association between the variables, and it assumes that the variables are nominal.

Annexe 4: Example of The Semi-Structured Interviews

Below is an example structure of the semi-structured interviews conducted during the field trip in October and November 2022 in the Ambanja district. The interviews were conducted with owners of PUEs. The questions were asked in English, translated into French by a Nanoé employee, and further translated into Malagasy by a local entrepreneur. The question below is only indicative but could evolve based on the answers within the interview.

INTRODUCTION

- first, I would like to **thank you** for taking the time to support us in this study.
- We **appreciate your cooperation** very much.
- *Brief **introduction of everyone***
- *Introduction: Tim and Nikolas: Tim and Nikolas work as research associates at the Technical University of Berlin. They work on electrification projects and the improvement of energy services in rural areas.*
- Please allow me to briefly **introduce the research, on which we are working.**
- **SHOW POSTER**
    - The interview takes place in the framework of a research and innovation project implemented by African and European partners.
    - The name of the research project is **„ENERGICA "**

- The **overall aim** of the research project is to develop smart energy solutions to decarbonize energy systems and provide access to energy through developing nano-grid solutions in Madagascar.
- In these nano grids we aim to integrate productive uses of energy, such as electrical rice hullers or freezers.
- The objective of this interview is to identify potential uses, appropriateness, and probable energy consumption patterns of such productive uses.

- I would like to say a few words about the **structure of the interview**.
- The interview will have **two parts**.
- The **two parts have different kinds of questions** and at the beginning of each part I will explain the specifics in more detail.

- Check **time availability.**

- Before we proceed onto the first question, in which I will ask you to introduce yourself, I would like to ask for your **permission to record this interview. The recordings will in no way be made public.** This will allow us a detailed analysis of the outcomes. Do you feel comfortable with this?
- **START RECORDING**
- And can you be **quoted**?
- Furthermore, I would like to point out that you may withdraw from this interview at any time.
- Do you have any **questions**?
- If you are ready, I would like to **start** with the first question?

INTERVIEW QUESTIONS - PART A

For the very first question, I would like to briefly ask you introduce yourself.

A.0 Could you briefly introduce yourself?

[Introduction part A]

In this first part of the interview, we would like to ask you some broadly framed questions to gain fundamental insights into the research subject. You may take time to answer the questions comprehensively.

A. OWNERSHIP & Value Streams

A.1 Do you currently process rice manually or by using any energy sources?
[if energy sources]: What energy source do you use?
A2. Do you own the rice huller, or do you share the ownership with other community members?
IF shared with community members
A2. C
A2.C Financing

A2.C.F i) How did you finance the rice huller?
A2.C.F ii) Where did you purchase the rice huller?
A2.C.F iii) How much did you pay for the rice huller?

A2.C Operation

A2.C.O i) How many people do you share the rice huller with?
A2.C.O ii) How do you coordinate the operation of the rice huller amongst the owners?
A2.C.O iii) At what time of the day is the rice huller in use?
A2.C.O iv) At what day of the week is the rice huller in use?
A2.C.O v) Does the usage of the rice huller vary with seasonality?
A2.C.O vi) How much rice does the rice huller produce per day?

A2.C Product flow

A2.C.P i) Do you buy the paddy rice or grow rice yourself?
[if buy]: What is the price for paddy rice?
[if buy]: Where do you buy the rice?
A2.C.P ii) Do you sell white rice?
[if yes]: What is the current market price for white rice?
[if yes]: Where do you sell the rice?
A2.C.P iii) What do you do with the rice husks?

IF exclusive ownership

A2.O

A2.O Financing

A2.O.F i) How did you finance the rice huller?
A2.O.F ii) Where did you purchase the rice huller?
A2.O.F iii) How much did you pay for the rice huller?

A2.O Operation

A2.O.O i) Who operates the rice huller?
A2.O.O ii) At what time of the day is the rice huller in use?
A2.O.O iii) At what day of the week is the rice huller in use?
A2.O.O iv) Does the usage of the rice huller vary with seasonality?
A2.O.O v) How much rice does the rice huller produce per day?

A2.O Product flow

A2.C.P i) Do you buy the paddy rice or grow rice yourself?
[if buy]: What is the price for paddy rice?
[if buy]: Where do you buy the rice?
[if not buy]: Do people pay you for processing their rice?
A2.C.P ii) Do you sell white rice?
[if yes]: What is the current market price for white rice?
[if yes]: Where do you sell the rice?
A2.C.P iii) What do you do with the rice husks?

[Introduction part B]

In this second part of the interview, we would like to ask you some open questions to gain your personal insights and understand your point of view. You may take time to answer the questions comprehensively.

B. Personal Experience

B.1 How much rice does your household you consume per day/week/month?
[if answered]: How many people live in your household?
B.2 What is the typical market price for white rice?
B.3 Do you experience problems in the supply with rice?
B.4 Do you experience problems in the processing with rice with the current rice huller?
B.5 What would you like to improve with the current rice huller?
B.6 What would you think of a rice huller powered by renewable energy, e.g., photovoltaic?

SUMMING UP

- Is there anything you would like to add?
- Do you have any questions?
- Can we look at the rice huller?

Thank you!

Annexe 5: Energy System Modelling

The Open Energy Modelling Framework is a generic, open-source toolbox that can be applied for the modelling and optimizing of energy systems. It is programmed in the object-oriented programming language Python. Oemof is based on a generic approach, which facilitates custom modifications and adaptions according to the user's requirements. Here, we only provide a description of the linear problem formulated to optimize the energy systems.

Linear programming is a mathematical optimization approach consisting of the formulating a linear equations system to calculate the maximum or minimum value for a linear function, which states the objective function. The objective function may be subject to a set of linear constraints, which are formulated also as equations or inequations and limit the possible solutions. The objective of the optimization formulated in the present study is to minimize the total annualized cost TAC of the investigated energy system. The objective function is defined as follows:

Equation:

$$TAC = \sum_{i\in N} a_{invest,i} * CAP_{invest,i} + \sum_{t} \sum_{(i,b)\in N} c_{var,i} * E_{ib,t} \; \forall\, c \in C, t \in T$$

, with $a_{invest,i}$ as specific annuity per installed capacity of component $i \in N$, the capacity $CAP_{invest,i}$ of each component $i \in N$ and the energy flow $E_{ib,t}$ from component i to bus $b \in N$ during each time step $t \in T$. N denotes the set of all nodes (components und buses) while T represents the set of all time steps (8760 h). The specific annuity per installed capacity is calculated via Equation 9:

Equation:

$$CRF + opex_i$$

, in which $capex_i$ are the CAPEX of the per-unit costs for each component, CRF is the Capital Recovery Factor and $opex_i$ are the operation and maintenance costs per unit and year. The $capex_i$ are calculated via.

Equation:

$$capex_i = c_i + \sum_{R} \frac{c_i}{(1+d)^T} - \frac{c_{res,i}}{(1+d)^n}$$

, in which c_i is the investment cost of asset i $c_{res,i}$ the residual value of component i, n the year of replacement of a component i, and T the project duration. A draft illustration of the objective function input data and intermediate calculations is given in Figure 15:

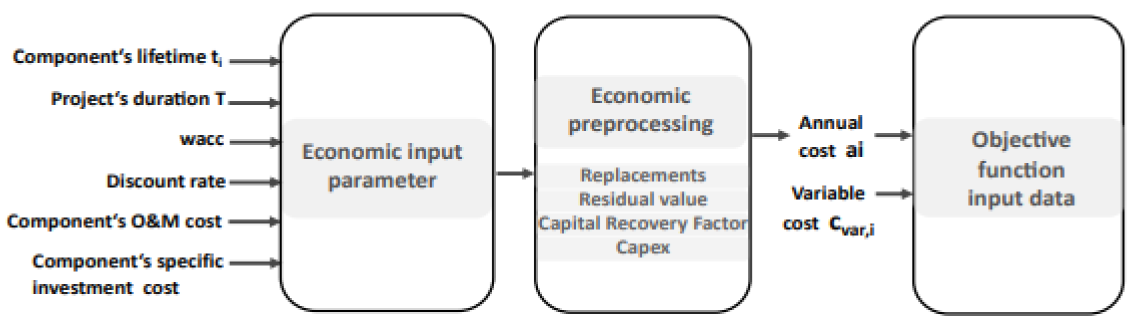


Figure 25: Objective function input Data and economic pre-processing to calculate specific annual cost per installed capacity

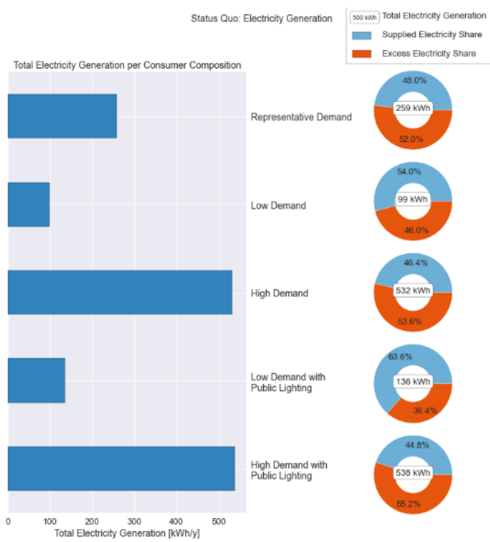
The key generic entities of oemof are source, transformer, sink, bus, and Generic Storage. Table 7 includes the characteristics of the key entities. The classes related to the generic entities are provided by the key library Oemof-Network. The connections between the components and the buses are described by flows based on the class flow from the Oemof-Solph package. By means of the generic characteristics, it is possible to set up a specific energy system accordingly to the modelers' requirements by defining several numbers of inputs or outputs with certain properties. The calculation of the inputs and outputs is based on mathematical equations and conversion factors.

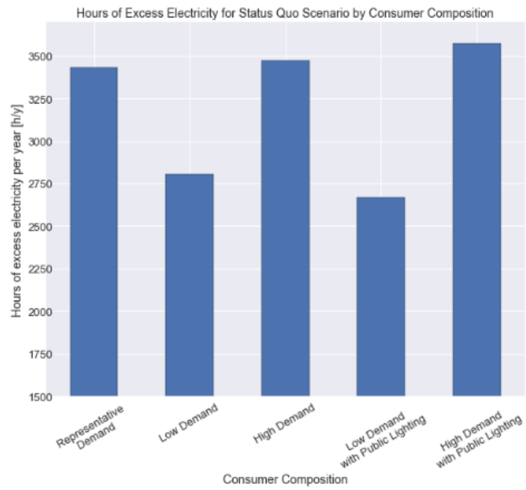
Table 7: Generic components in oemof

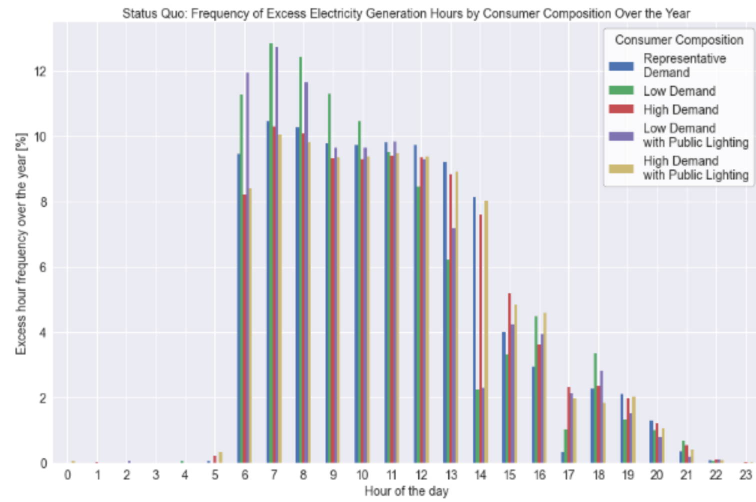
Class	Features	Example/use
Source	• Generic source to bring flows into the energy system model. • No inputs, n outputs • Can include costs	Solar arrays, wind power, coal power unit
Sink	• Generic sink to export flows from the energy system model • N inputs, no outputs • Can include costs or revenue	Power demand, Heat demand
Transformer	• Generic conversion unit • N inputs, m outputs	Power-to-gas converter, diesel generator, rice huller
Generic Storage	• Generic storage unit which inherits from the Transformer class	Battery, Hydrogen tank
Bus	• Generic element to balance all out- and inflows, inputs, outputs	Grid or network without losses

Annexe 6: Technical Modelling Results

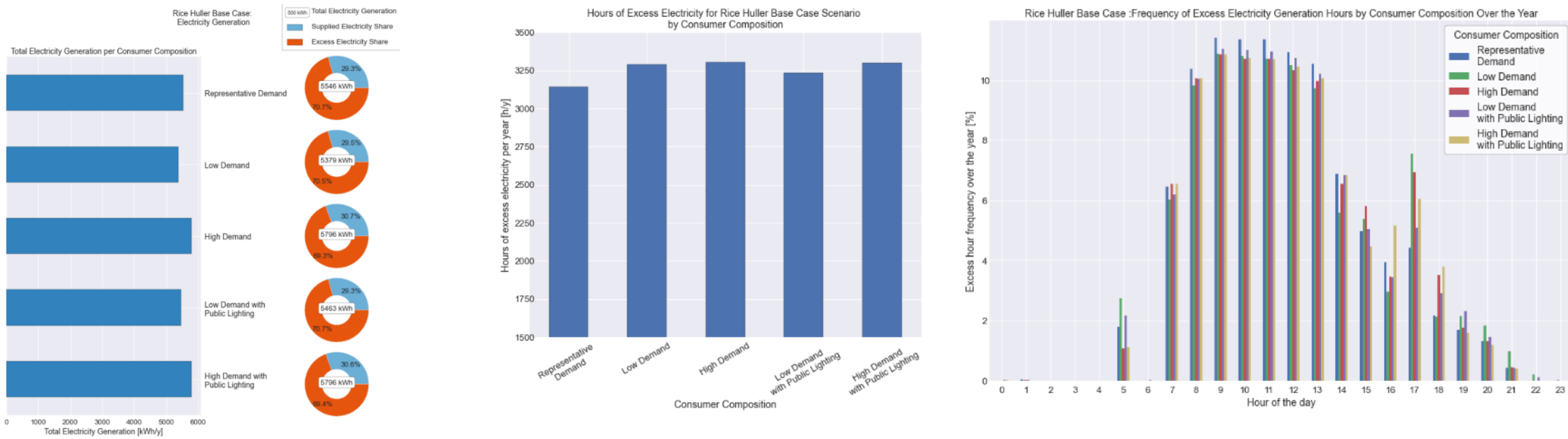
a) Base case nano grid



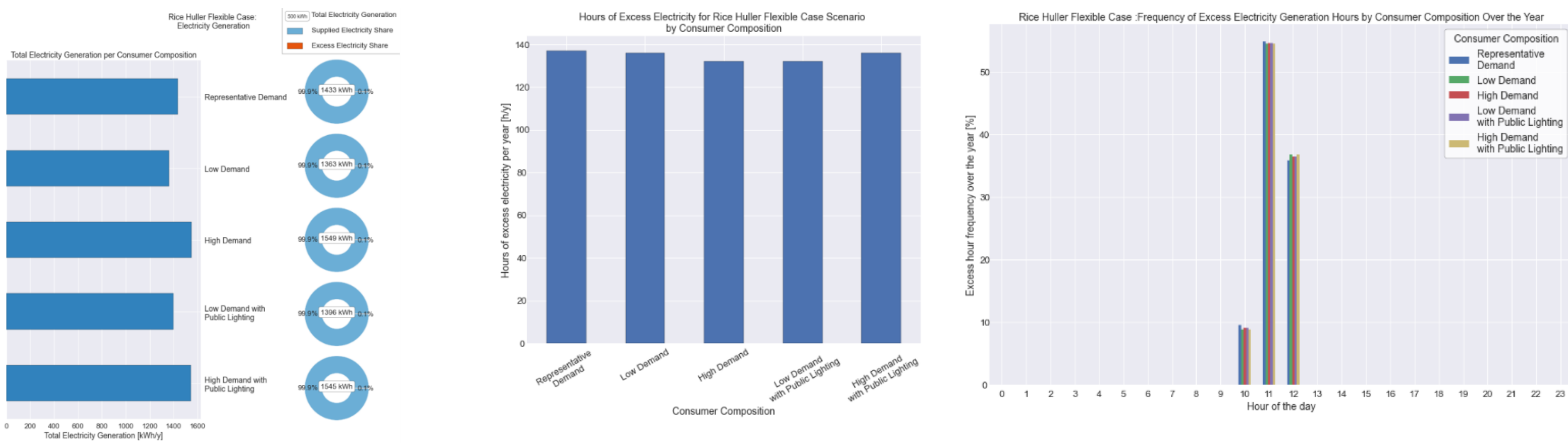




b) Rice huller integration



c) Flexible rice huller integration



d) Freezer integration

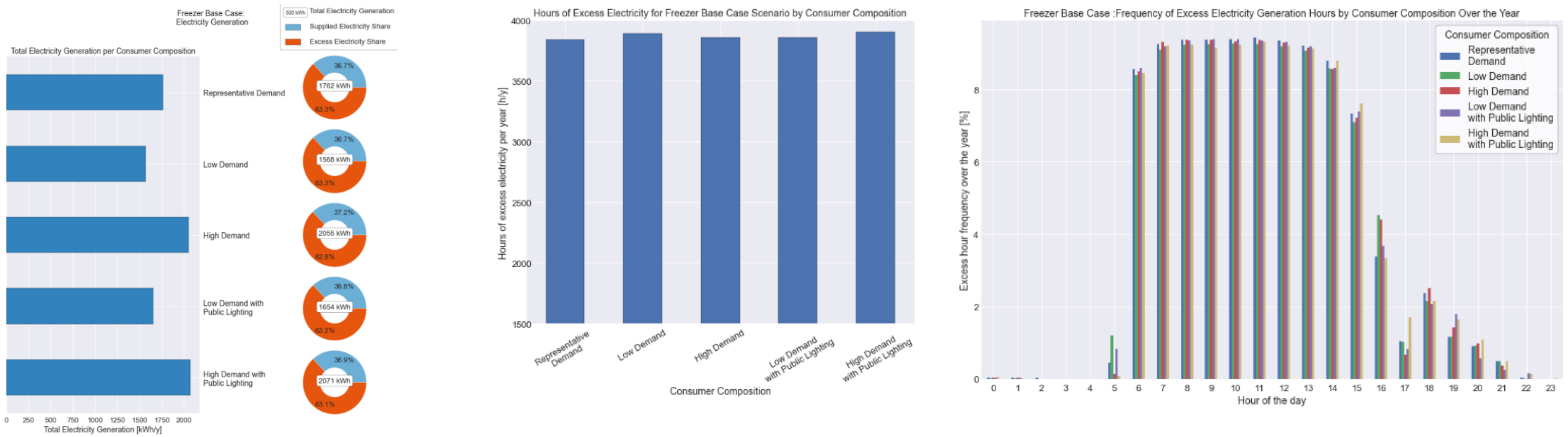
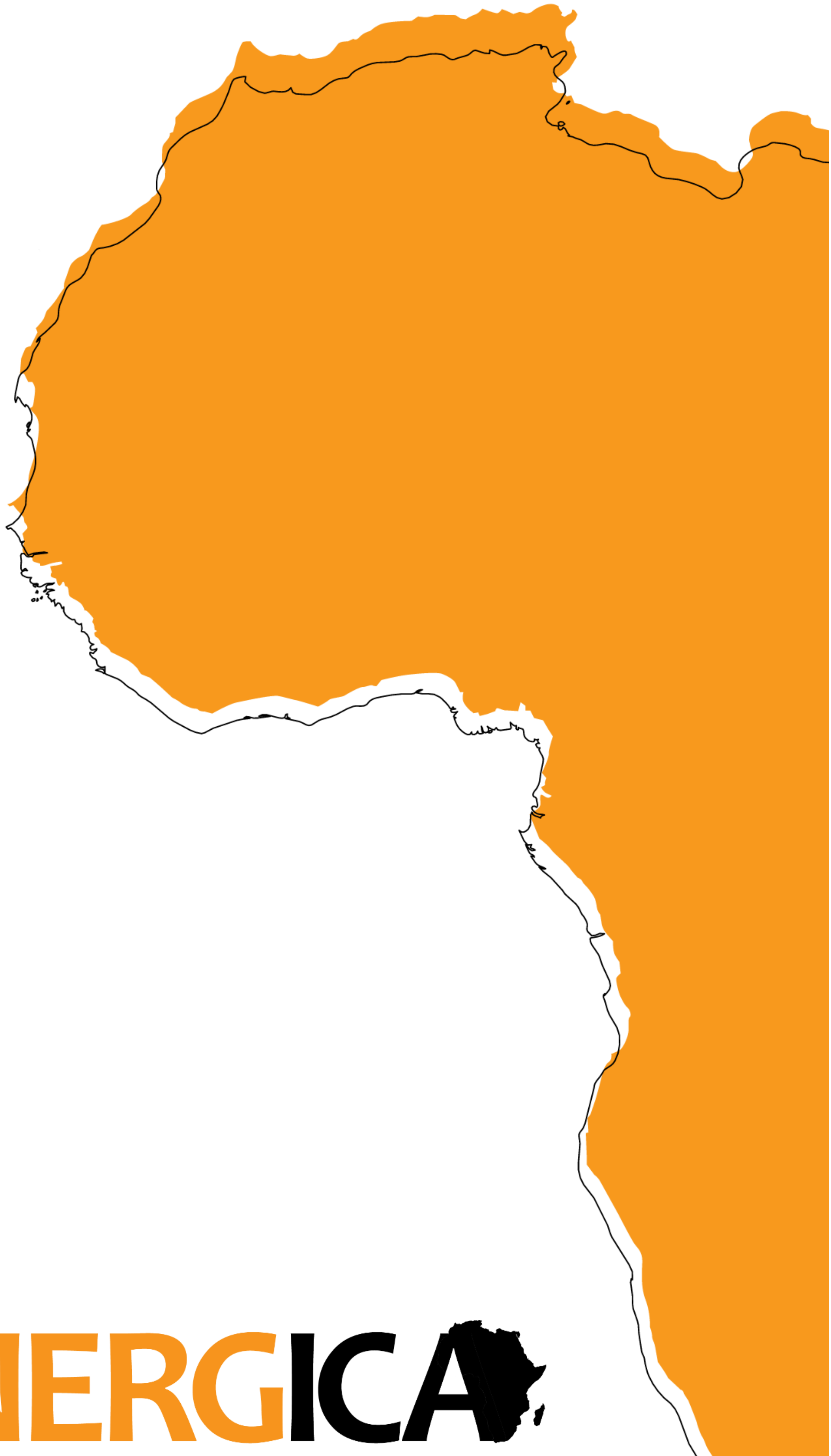


Figure 26: Share of excess electricity (left), total hours of excess electricity (middle) and daily distribution of hours with excess electricity (right).



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