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Matchmaking in Off-Grid Energy System Planning: A Novel Approach for Integrating Residential Electricity Demands and Productive Use of Electricity

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Abstract: Off-grid electrification planning increasingly recognizes the importance of productive use of electricity (PUE) to promote community value creation and (financial) project sustainability. To ensure a sustainable and efficient integration in the community and energy system, PUE assets must carefully be evaluated to match both the community needs and the residential electricity demand patterns. We propose a novel methodology interlinking qualitative interviews, statistical analysis, and energy system modelling to optimize decision-making for PUE integration in off-grid energy systems in rural Madagascar by aligning relevant PUE effectively with anticipated residential electricity demand patterns based on socio-economic determinants of the community. We find that a possible contribution of the PUE to reducing the electricity costs depends significantly on three factors: 1. the residential electricity consumption patterns that are influenced by the socio-economic composition of the community, 2. the degree of flexibility of i) PUE assets and ii) operational preferences of the PUE user, and 3. the capacity of community members to finance and operate PUE assets. Our study demonstrates that significant cost reductions for PUE-integrated off-grid energy systems can be achieved by applying our proposed methodology. When matching PUE and residential consumption patterns, the integration of PUE assets in residential community energy system *can* reduce the financial risk of operators, provided the PUE enterprise operates reliably and sustainably. We highlight that the consideration of local value chains and co-creation approaches are essential to ensure the energy system is addressing the community's needs, creates value for the community, enhances the project´s financial sustainability, and is achieving the overall objectives of decentralized energy system planning.

Keywords: rural electrification; productive use of electricity; off-grid; community energy; energy system planning; sustainable development; key informant interviews; energy system modeling; statistical analysis; co-creation

1. Introduction

1.1. Background and Theoretical Foundations

Ensuring reliable and affordable access to electricity is paramount for households and communities to attain fundamental capabilities [1]. The useful energy services associated with adequate access to electricity are a cornerstone for economic development [2,3] but are also indispensable for advancement across diverse dimensions, i.e., education, nutrition, sanitation, and health [4–6]. Furthermore, access to electricity is a sociotechnical imperative, fostering social innovation that is pivotal in facilitating a low-carbon energy transition, promoting civic empowerment, and addressing overarching social objectives [7].

On the global political stage, the acknowledgement of the critical role of universal access to electricity is reflected in target 7.1 of the Sustainable Development Goals (SDGs), adopted by the United Nations in 2015 [8]. While notable progress has been documented in the preceding decade, the realization of universal electrification by 2030, as stipulated within SDG 7.1, remains at a considerable distance. Globally, more than 675 million people lacked access to electricity in 2021 [9]. Rural regions are disproportionally affected, with eight out of ten people without access living in rural areas [9]. In Sub-Saharan Africa, where 567 million people lacked access to electricity in 2021, the disparity in electricity access rates between urban and rural areas has risen in recent years [9]. This trend can be attributed to the financial and technical challenges of reaching the rural population. In rural areas that are only sparsely populated and where purchase power and electricity consumption can be low [10], extending the national power grid to supply electricity is economically often not viable [11]. Here, isolated renewable-based off-grid systems can be a cost-efficient and sustainable solution to enable electricity access to communities (e.g., [11–14]) and provide communities a basis for conducting activities that enhance development across the various dimensions interlinked with electricity (see, e.g. [2,6,10,15]).

More granular research on the interlinkage of access to electricity and development on the micro-level (see, for example, [16]) has shown that while access to electricity via off-grid energy systems *can* stimulate development in rural communities, access to electricity alone does not guarantee development. One must note that literature assessing a correlation between electricity access and development often ascribes economic metrics as a central effect measure for development, e.g., household income [e.g. [16,17]]. Given the significance of household income for causally related household activities that may lead to changes evoking development in other dimensions [17], this is a meaningful indication. Nevertheless, evidence of projects, in which access to electricity in rural locations was enabled and no direct effect on income or well-being was observed, is abundant (e.g. [18]). In fact, the impact of electrification projects on enhanced development (i.e., increasing economic activities or household income) seems to crucially depend on the community's *choice* of how to *use* the electricity within the scope of action that is facilitated by the local energy system. Thus, literature evidence is strong that the outcomes and impact of electrification projects (note that in this paper, we understand as per the logical framework theory 'outcomes' as the project´s effects at the target-group level as opposed to 'impact' as project´s effects at the societal or regional level) depend on i) the *ability* and *choice* of the community to *use* the electricity for *productive activities* [19,20] and ii) external factors supporting the community in their *capacity* to *utilize* electricity for productive activities, e.g., finance, training, awareness, etc. [15,17], and iii) the degree to which the energy system design facilitates the community´s choices.

The use of electricity for productive uses is commonly referred to as productive use of electricity (PUE) as opposed to consumptive use of electricity in households [19]. Such PUE commonly is electrically powered machinery used by the community, according to their operational preferences, and may be directly integrated into the electricity supply system that serves residential loads of the community. Thus, the PUE appliances and the user of the PUE asset directly influence the operational requirements of the electricity supply system and its financial viability. Energy system planners (note that we use the term "energy system" instead of "electricity system" to account for potential additional energy vectors in the system) pay increasing attention to PUE system integration and PUE user behavior. In addition to supporting the stimulation of the economic and social development of the community or individual user [15,17], PUE appliances *can* benefit the financial viability of the energy supply system. PUE appliances typically consume more energy than residential appliances in rural villages [21,22] and therefore may pose a reliable (and relatively larger) source of income for the system operator compared to domestic loads (see relevant discussions on 'anchor loads' as relatively large non-domestic loads in [23]). Prominently, the financially viable operation of off-grid energy supply systems that serve residential customers with a low electricity consumption poses significant challenges. Including PUE assets as anchor loads can increase the energy system utilization rate and provide a predictable high off-take guarantee, which in turn improves the projects' bankability [21] and de-risks electrification projects for the private sector [10]. One must note that the prevailing

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narrative in the relevant literature that PUEs are a reliable and relatively higher source of income for rural electrification operators ('anchor load') is not universally applicable and depends on the respective context. In rural businesses that are often operated by single informal entrepreneurs and may not be well organized, the operation of PUE may in fact be erratic. In addition, the continuous electricity demand of the PUE asset depends on the economic success of the associated business. The dependency poses a financial risk to the energy system operator. This is especially relevant in contexts that are characterized by short lifetimes of businesses. Nevertheless, in communities with limited financial capacity to invest in stand-alone energy systems that power PUE asset, the systematic planning of integrated energy system serving both PUE assets and residential loads is imperative for the utilization of electricity for productive uses and the development of associated capacities within the community.

The essential aim of off-grid energy system planning is to design a system that adequately addresses the electricity-related needs of the community it serves. In this, the system must be financially viable to sustainably be operated and maintained to ensure it´s proper function. ***Figure 1*** describes basic dynamics and interactions between local parties involved in and relevant for the description of the considerations that guide the planning of an off-grid energy system that integrates domestic household loads and PUE loads.

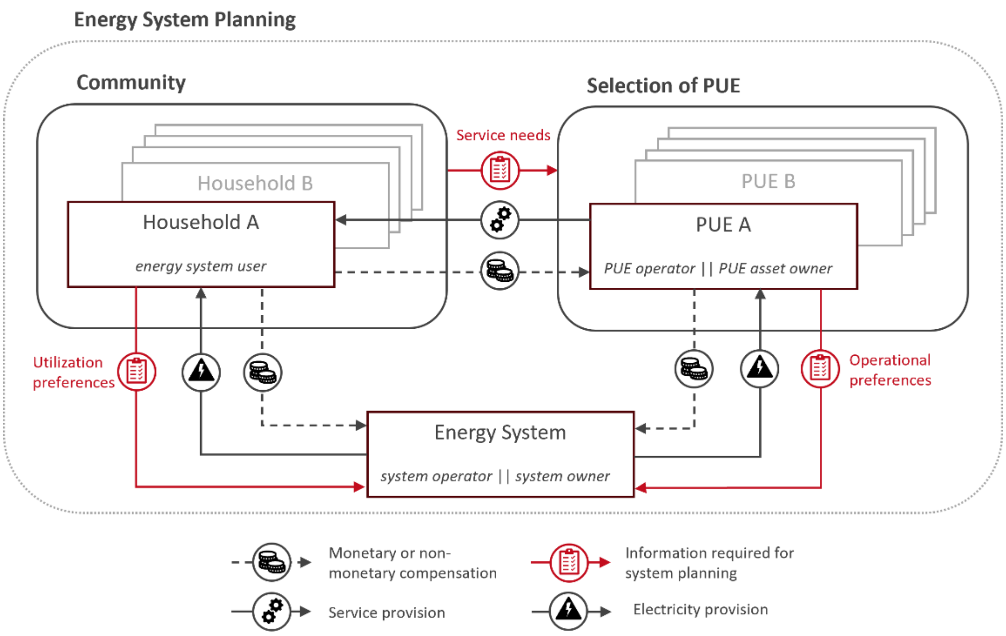

Figure 1. Conceptual considerations for the integration of PUE and household electricity demands in off-grid energy system planning.

The community is composed of individual households using the energy system. These households have individual time-variable preferences and capabilities (i.e., assets) to utilize electricity. Within the community there are needs for services, some of which can be supplied by specific PUE that can be integrated in the local electricity supply system. The electricity and service needs are highly context specific. The electricity utilization preferences of the individual households and the operational preferences of the PUE operator determine the principal design requirements for the integrated energy system. For the energy system and the PUE two roles are relevant, namely the role of operation and the role of financing and ownership. These roles may be taken by the community, a single member of the community or an external entity, including the energy system planner.

We make use of Figure 1 to both guide the discussion of existing literature and its respective underlying perspectives, and to describe the deliberate assumptions we made in our analysis. In research and in the practical implementation of project the planning rationale deviates from a generalized perspective. For context-specific relevance it is useful to deviate from a generalized consideration, presume system design choice and make context-specific assumptions. The assumptions made may be a result of limitations of available data, e.g. the household electricity demand, or may result from the intention to study certain underlying dynamics or the consequences of specific system choices e.g. applicable business models. In practice the basis for decision-making is in many cases the financial viability of the energy system, as rural electrification efforts are often driven by the private sector that requires a cost recovery business model. It is important to note that this constitutes a specific perspective, namely system financing and operation. Accordingly, the current literature investigating the integration of PUE in off-grid systems supplying electricity to household loads often and usefully takes the financial perspective and evaluates the integration of PUE in off-grid systems based on it's expected financial impact. Given the complexity of and the various possible constellations of interaction and behavior of parties involved in the local energy system as depictured in Figure 1 it is no surprise that the existing literature finds contradictory results regarding the financial benefits of integration of PUE in off-grid energy system. For example, Booth et al. [24], in a hypothetical community microgrid scenario (peak load of 5.7 kW), find that integrating a single 10-kW maize mill could either decrease the cost of electricity provided the system by 14% or increase it by 7% compared to a system only serving domestic loads, depending on the mill's daily and seasonal operational parameters (notably, the authors exclude the costs of the mill from their calculation, assuming any community member or external party taking the role of PUE financing). Specifically, the authors find that the economic impact of integrating the maize mill varies across 'operating scenarios', which denote different usage patterns of the mill across days of the week or seasons of the year. Similarly, van Hove et al. [21], studying the economic impact of integrating various PUE in mini-grids serving household loads, find that the impact is determined by the usage patterns of the PUE. Especially seasonally used PUE may offer only little improvements of the system costs, as they require additional energy system assets to meet peak demand in the high season that under-utilized during the low season [21]. These two examples (for other similar examples see [25,26]) support our suggestion that to ensure economic improvements of off-grid electricity supply via integration of PUE the energy consumption patterns of the PUE appliances (notably determined via usage patterns and community preferences) need to fit into the household residential electricity consumption patterns to avoid costly additional production (and storage) devices being required to power the PUE aside from the residential loads.

1.2. Motivation and Ambition

Supported by this evidence, we determine that an economic benefit when integrating PUE in energy systems will only substantiate for all parties involved when i) the PUE asset integrated in the system addresses service needs of the community – thus, being used and consumes electricity sustainedly, ii) the electricity load patterns of the PUE and residential loads – each determined by the individual community member using the respective load – enable operational synergies and iii) the energy system infrastructure is flexible enough to accommodate varying demand conditions (i.e., measures to efficiently add or remove production, storage and distribution assets). Thus, energy system planners integrating PUE in off-grid systems simultaneously serving residential loads are challenged to identify PUE that are relevant to meet the services required by the local community (**Challenge I**) and identify PUE with load profiles that do not conflict with the domestic household load profiles (**Challenge II**). While the first may be solvable by observing local value streams of the communities, the latter poses a significant challenge. To identify a well-fitting PUE for a residential system, practitioners often ex-post integrate PUE within existing residential off-grid energy systems to use historical data of the system under consideration or similar systems to identify PUEs matching the current residential energy consumption. However, historical data of residential users in off-grid energy systems are often not available, not generalizable [27] or require complex processing. Therefore, practitioners rely on trial and error, often ending up with inefficient solutions and energy systems ill-suited to their application [27]. Further, ex-post integrating PUE in existing residential systems may hinge on decisions taken in conceptualizing the residential system that poses inefficient path dependencies for the entire PUE system. For example, if the primary energy generation asset has already been fixed, it may be inefficient to install additional production equipment required to supply the PUE appliance, which could potentially have prevented the simultaneous scaling of the residential and PUE systems (**Challenge III**). Third, it is well known that the usage patterns of PUE appliances, dictated by the activities and behavior of residents using the appliances, can affect the requirements of the system components, scaling, and, therefore, economics [21]. Co-creating an energy system with the PUE user and residential energy system users (see ***Figure 1***) may unlock cost savings that cannot be achieved when ex-post integrating PUE systems. While such a co-creation approach is increasingly discussed in the academic literature (see e.g., [28,29]), it is rarely used in practice. However, in fact, energy system users – i.e., community members - are implicitly included in system conceptualization by energy system planners at the beginning of the conceptual design of energy systems (e.g. by assuming consumption patterns based on previous experience etc.); but are not comprehensively be integrated in the planning process. The potential of fully integrating co-creation approaches in energy system are yet to be explored (**Challenge IV**). A maximum participation of the (future) users - as will be discussed in this paper - can contribute to optimally aligning the various electricity consumptions in a system - dictated by user behavior - with the planned energy system assets to minimize the energy supply costs and as a result also minimize possible energy costs for the users.

Therefore, in this paper, we propose a methodology to tackle prevailing challenges in energy system planning for off-grid electricity systems to cost-efficiently design off-grid energy systems, including PUE, improve the project's financial viability and increase the potential contribution of electricity access to enhance development of the electrified communities. We therefore aim to address the following challenges:

Challenge I: Identify a PUE appliance that meets the services required by the local community and guarantees sustained usage and electricity consumption

Challenge II: Identify PUE appliances with load profiles that do not conflict with the residential load profiles with the aim to improve the financial viability of the project via PUE integration

Challenge III: Design an energy system that serves both residential loads and the PUE appliance to make use of synergies

Challenge IV: Showcase the potential for energy system cost reduction that can be achieved by matching the user behavior of PUE and of household appliances when co-creating energy systems with its users.

Our methodology combines qualitative interviews, advanced statistical analysis, and energy system modeling. First, in a community in Madagascar, we identify relevant PUE assets that address the community's service needs, the associated value streams, and the associated operational patterns. Next, we use historical data of residential nanogrid energy systems to study the development of electricity consumption over time, identify statistically significant predictors of electricity consumption, and derive representative load profiles. Subsequently, we apply energy system modeling to model scenarios of integrating PUE appliances with representative residential load profiles that represent socio-economic characteristics and optimize the models with regard to the lowest total system costs, including investment decision in energy system assets and PUE, and their dispatch. We evaluate the results based on key economic and technical metrics. By interpreting the key figures, we can derive statements regarding the suitability of matching different PUE appliances with households based on their socio-economic and demographic description. In addition, we can observe the distributional effects of cost-sharing between residential electricity users and PUE users across different PUEs.

The methodology was developed in a case study of a rural village in northern Madagascar, and two PUE appliances were exemplary assessed (an electric rice huller and freezer). We provide evidence from semi-structured interviews with local communities to calibrate the model and derive additional qualitative evidence of PUE integration in energy system planning.

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2. Materials and Methods

We first provide an overview of the setting of our case study (Subsection 2.1). Subsequently, in Subsection 2.2, we describe the generalized and replicable methodological workflow of our analysis. We explain the respective methods and the data used in each step of the workflow in detail within the Subsections 2.1.1 – 2.1.5.

2.1. Case Study

The methodology was developed based on a case study encompassing data from the village Ambohimena in the Diana region in northern Madagascar. The overall electricity access rate in the Diana region is estimated at 5% (national average overall 35%, rural: 10.9% in 2021 [30]. Increasing electrification in the Diana region is challenged by the predominant settlement patterns. Aside from a few densely populated (and electrified) cities, the population density is low, dominated by small villages with households closely built. Hence, small scale grids connecting a few households is seen as an economically reasonable pathway for electrification.

Ambohimena is near the mangrove forests and is set along one main road that is unpaved and is connecting the cost with the city Ambanja. In contrast to other villages in the region, the village is accessible via car and motorbike during the most time of the year. In Ambohimena electricity is available primarily through the services of the locally-based company Nanoé, which offers electricity supply via direct current (DC) PV-battery hybrid nanogrids. The nanogrids typically connect 3-5 households with 100 Wp – 200 Wp installed PV and 90Ah or 130Ah battery storage capacity. Ambohimena was chosen as a case study because i) historic residential electricity consumption patterns of nanogrid users are available, ii) socio-economic data of residents are available, iii) residents of the village could be interviewed during a field trip conducted in October and November 2022.

2.2. Methods

As part of this study, a novel methodological workflow was developed to evaluate different PUE's technical and economic fit with residential household energy consumption patterns based on the residential community's socioeconomic and demographic composition. **Figure 2** illustrates the proposed methodological workflow. The workflow is divided into five steps, for each of which the applied methods and integrated data are described in detail in dedicated Subsections (Subsections 2.2.1 – 2.2.5).

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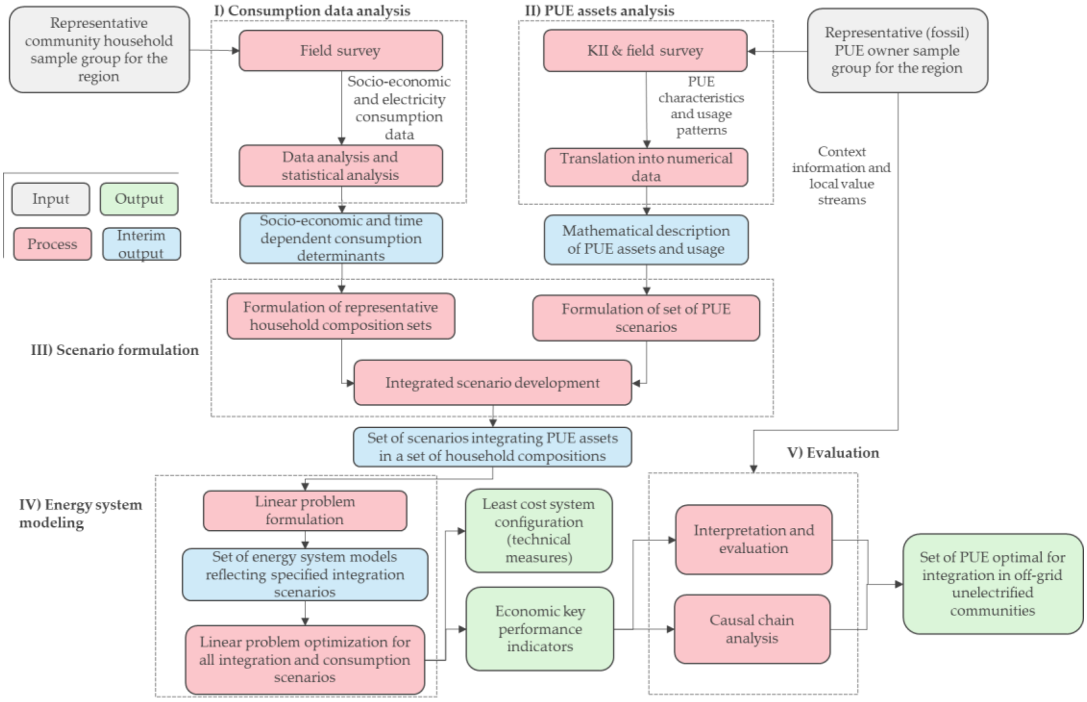

Figure 2. Methodological workflow of the analysis.

2.2.1. Consumption Data Analysis

Our methodology relies on thoroughly assessing historical electricity consumption patterns of a representative residential community connected to a nanogrid. The consumption data analysis aims to identify i) time-dependent determinants of residential electricity consumption patterns (based on power and energy demand on hourly resolution) and ii) socio-economic and demographic determinants of electricity consumption patterns. 107 village residents currently connected to nanogrids were chosen as the sample size for the study due to the consistency of electricity consumption data and socio-economic data. The following data was used:

- Electricity consumption data: to reconstruct historic hourly electricity consumption patterns, the sample's electricity current measurements (10 minutes resolution) between January 2018 and December 2021 (Earliest data point: 10.02.2018. Latest data point: 01.12.2021) were multiplied with measured voltage (hourly resolution) and interpolated. The data was cleaned to cover for eventual reboot events of the electricity consumption logging system or other missing values and passed to a Python-capable environment for further processing.
- Socio-economic and demographic data: we used socio-economic data from irregularly conducted household surveys conducted by Nanoé in 2018 – 2021 for the purpose of assessing potential nanogrid clients. As the surveys at that time were not intended to be used for a thorough statistical treatment to identify socio-economic predictors of energy consumption patterns, only a few useful characteristics were assessed (this poses a major aspect to be improved in future work within this research). However, to develop the methodology, we relied on this survey data. The surveys were conducted with any household resident available with the option to reject the answer to any question. Characteristics assessed (indicating the descriptive statistics of only valid answers in brackets behind) include housing occupant status (74,7% owner, 5% tenant), number of adults (median (Md): 2), number of children (Md: 2), monthly income (Md: 150,000 Ar ~ 30 €), housing wall type (Ravinala wood (40%), wood-concrete structure (18%), concrete/stone (22%), tin (2%)), housing roof type (tin (73%), leaves (9%), concrete (1%), floor type (concrete (77%), board (4%), appliance ownership (LED bulb, LED spot, TV, USB phone charger, 12 V plug), profession of the client (grouped into a trader (22.2%), farmer (31.6%), employee (6.8%), other (6.8%), public lighting (32.5%)). Notably, “public lighting” was included as a ‘profession’ by the stated purpose of electricity use in the client data. In addition to the socio-economic and

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demographic data, the historical tariff subscription option of residentials was identified from records. Notably, to mitigate the fact that data availability limitations within tariff records, we applied a machine leaning algorithm to calculate tariff subscriptions based on a multi-class problem. A detailed description of the method and it´s application in our analysis is available in the public project report [31]. For a description of the tariffs see Appendix Table A1.

We use advanced statistical analysis to identify socio-economic and demographic determinants of electricity consumption patterns, including preferred tariffs. First, we apply cluster analysis to historical electricity consumption data to identify common clusters of representative annual electricity consumption patterns. K-means clustering was used as the clustering method. K-means clustering is a machine learning algorithm used to partition a given dataset into k clusters based on the similarity of the data points [33]. It effectively identifies similarities between numerical data, defining distinct groups of patterns [33]. K-means clustering does not require uniform cluster densities and allows for multiple dimensional data [34]. Before applying the sensitive-to-outliers k-means algorithm, the data must be cleaned from outliers and re-scaled. Common min-max normalization was applied: Compared to other kinds of cluster analysis, the main shortcoming of the method is the challenge of pre-determining the appropriate number of clusters [34]. However, this drawback can be overcome by calculating similarity measures (silhouette score) [35]. Given that the data comprises numerical data, we use Gower as a dissimilarity measure (for mathematical equations see [36]).

Having established representative clusters of annual electricity consumption patterns within the representative sample group, we aim to identify socio-economic and demographic characteristics that can be used to predict the electricity consumption behavior of a specific community resident. Thus, we search for statistically significant predictors for cluster membership. Therefore, we use the Chi-square test or Fisher exact probability test (depending on the type of underlying variable) to identify socio-economic characteristics that significantly often occur within the distinct load profiles. The Chi-square test of independence, a nonparametric method, assesses the potential association between two categorical variables in a contingency table [37]. The test involves organizing variables into rows (variable i) and columns (variable j), with cells containing the total count of cases for each category pair. By comparing observed counts (o_{ij}) to expected counts (e_{ij}) for the sample size, the significant difference between expected and observed counts can be calculated (for mathematical equations see [38]). If the resulting X^2 is greater than the redefined critical X^2, the null hypothesis of independent variables may be rejected [37].

Like the Chi-square test, the Fisher exact test can assess the significance of the relationship between two categorical variables. The test calculates the probability of obtaining the observed distribution of frequencies or more extreme ones, assuming that the row and column marginal totals are fixed (i.e., the marginal totals are the same as those in the observed data). The Fisher's exact test provides an exact p-value, making it suitable for situations where the chi-square approximation might be unreliable due to small sample sizes [39].

The Chi-square test and the Fisher exact test assess the significance of the relationship between two variables. However, to quantify the strength of the significance, we calculate Cramer´s V, which is a normalized version of the Chi-square statistic. Cramer´s V effect size takes values between 0 and 1 with increasing relationship strength. Values up to 0.1 indicate weak association, values around 0.3 indicate moderate association, and values around 0.5 or higher indicate strong association [36]. In addition, it is determined whether the variables are characteristic of a single group, thus allowing it to be distinguished from the other two.

As a final output of the consumption data analysis (Step 1), we have a set of representative annual residential electricity consumption load profiles, which can be predicted by the residential community's socio-economic and demographic characteristics (including preferred tariffs).

2.2.2. Productive Use of Electricity Analysis

As a critical challenge when aiming to integrate PUE in off-grid energy systems, services needed by the local community and the respective PUE asset delivering the service must be identified. On the one hand, this ensures that the PUE asset will be operated, and electricity will be consumed sustainedly. On the other hand, the identification of needed services is required to ensure value creation for and improved development of the local community. Thus, PUE services and assets, that are relevant for the given context, i.e., significantly intertwined within existing value streams must be identified and characterized. Further, potential usage patterns of the PUE must be assessed, including factors influencing possible alterations to usage patterns.

In the case under investigation, a market assessment revealed rice hulling and ice production as relevant activities to be targeted with PUE as of their current dominance and importance in the local value chains. A DC rice huller and DC freezer were identified as the respective relevant PUE, technically feasible to be integrated into nanogrids. The required characteristics of the technical assets were identified during semi-structured interviews with key informants in the study area that already own respective assets, or the fossil alternatives (i.e., diesel-based rice huller), local market analysis, and previous market assessments conducted by Nanoé. Semi-structured interviews with open-ended questions based on the guidelines of Witzel [40] were introduced as a tool for information acquisition to understand the context of the study and the complex correlation of local issues. The interviews were used to capture i) the status of PUE, ii) prospects of PUE, iii) local value chains, iv) community structures, and – essentially – v) time-dependent usage patterns of PUE. A detailed evaluation of the interviews can be found in the publicly available project report of the ENERGICA project [31].

The load curve of the DC freezer was obtained from historical consumption data of a freezer (type: Steca PF166-H [41]) operated in the Ambohimena village, used to produce ice and conserve juice. The load curve of the rice huller was estimated by observing usage patterns and product flows of currently used diesel-based rice hullers. The interviews suggest a substantial seasonal variation in the use of the rice huller, ranging from 1 h to 2 hours per day in the rainy season up to 9 hours a day in June, which is the peak month of the harvest season. Based on the monthly production of rice hullers assessed via a 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 would start at 6 am, as suggested by one interviewee, and finalize once the calculated output of the specific day has been reached (with a three-hour 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 and 11 am and again from 2 pm until 6 pm in June. The PUE's average daily electricity load patterns are illustrated in Appendix Figures A1–A3.

Due to time restrictions and the language barrier, it was only possible to record to a limited extent which factors, in addition to external influences, determine user behavior and to what extent user behavior is therefore variable. The answers received suggested that the user behavior of the rice huller is largely determined by the seasonal weather and vegetation cycles, but otherwise offers little flexibility.

We used Microsoft excel to transfer the information into numerical data and process the data. As final output of the PUE analysis, we established i) time series of the assumed electricity consumption over the year (8760 timesteps) and ii) technical and economic characteristics of the PUE assets as numerical data.

2.2.3. Scenario Formulation

In the scenario formulation, we perform the matchmaking of residential electricity consumption compositions and PUE asset electricity consumption pattern, as illustrated in **Figure 3**.

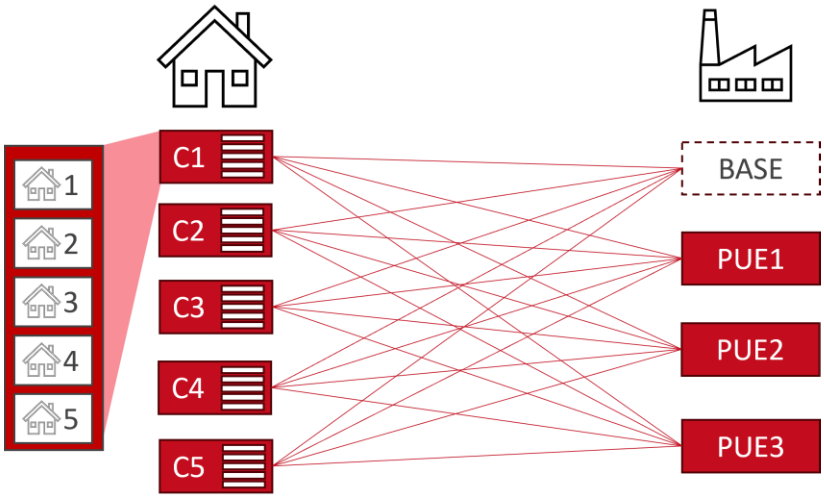

Figure 3. Scheme of the matchmaking performed, matching different residential electricity demand profile compositions with different PUE assets.

We first develop five distinct sets of residential nanogrids reflecting distinct residential community compositions as explained in Chapter 3. These differ in the constellation of the five residential load average profiles representing the respective electricity consumption pattern profile cluster identified during cluster analysis.

The five residential load sets will be matched with different PUE and respective load profiles. With this, we can derive valuable information on the fit of a PUE in specific residential energy systems, reflecting residents' distinct socioeconomic and demographic characteristics. Therefore, we match four PUE integration scenarios with the five distinct residential compositions. The PUE integration scenarios are (1) Base case residential nano grid without any integrated PUE according to the five distinct sets of residential load compositions (C1-C5 in **Figure 3**.), (2) integration of a rice huller in a nano grid with residential load profiles C1 – C5, (4) integration of a freezer, and (3) integration of an unconstrained and flexible in operation rice huller in a nano grid. While the interviews insufficiently assessed the flexibility of the users in adopting energy system beneficial usage patterns, we additionally introduce a scenario which offers 'total operational freedom' to the rice huller (4). In this "flexible operation" scenario, we only constrain for a minimum required yearly rice output. Notably, this scenario poses an unrealistic extreme. However, it reflects (extreme) adoption of the user behavior to respect energy system constraints.

2.2.4. Energy System Modeling

We apply computational energy system modeling to derive a quantitative basis to evaluate the fit of PUE and different residential electricity consumption profiles. Via energy system modeling we obtain technical (i.e., component capacity and dispatch) and economic (cost) information of how a nanogrid serving the included residential and productive loads would ideally be designed.

We rely on the open energy modeling framework (oemof). For a detailed description of the framework, see Hilpert et al. [42]. Oemof is based on a graph-based approach, setting components and buses into a mathematical relationship, holding both technical and economic numerical data. With this, we can establish a mathematical representation of the energy systems and underlying economic characteristics to perform an economic optimization. We establish a linear problem to be optimized. For this analysis, we apply the minimization of the total annualized energy system costs (including capital and operational expenditures) as objective function. We estimate economic and technical characteristics of energy system asset based on local market data and key-informant interviews as summarized in **Table *1*** and **Table 2**. The project lifetime was assumed to be 10 years, while the weighted average costs of capital (WACC) are estimated with 10%. Note that the WACC may significantly differ depending on the entity investing in the energy system, i.e., in a corridor between close to 0% for local private companies receiving funding grants and up to 30% for local individuals. As input data for a time series of PV irradiation in hourly resolution, we rely on the MERRA-2 dataset with the reference year 2019. Data was accessed via [43].

Table 1. Economic parameters of energy system assets assumed in the analyses. *According to a market available product [41]. **While re-fitting diesel-based rice hullers with a DC motor is tested within the ENERGICA project, the assumed costs are in line with commercially available DC products [44].

Component	$CAPEX_{fix}$	$CAPEX_{variable}$	OPEX
PV	101 €	540 €/kW	14 €/kW/yr
Battery	26 €	246 €/kWh	14 €/kW/yr
Supplementary components	306 €	-	9.2 €/yr
DC freezer*	1220 €	-	
DC rice huller**	-	607 €/kW	28 €/kW/yr

Table 2. Technical characteristics of energy system assets assumed in the analyses.

Component	Parameter	Value
PV	Lifetime	10 y
	Optimal tilt	-29° [45]
	Loss fraction	10% [46]
Battery	Lifetime	3.5 y
	Efficiency	0.8
	SOC min	0.3
	C-rate	C/10
DC rice huller	Lifetime	5 y
	Conversion rate electricity to rice flour	70 kg/kWh
DC freezer	Lifetime	10

2.2.5. Evaluation

To evaluate the modeled scenarios, we further compute technical and economic measures of the optimized energy systems. As economic measures, we calculate the levelized costs of the entire energy system (LCOS), levelized costs of residential electricity consumption ($LCOE_{Residential}$), and levelized costs of providing the PUE service ($LCOE_{Service}$). The LCOS reflect the average costs per kWh of useful electricity the system generates. We calculate the LCOS by dividing the total annualized costs (TAC) by the amount of electricity served $Electricity_{served}$.

$$LCOS = \frac{TAC}{Electricity_{served}} \quad (1)$$

The terminus $Electricity_{served}$ includes the total energy delivered, including residential and PUE loads. In contrast, the levelized costs of electricity for residential loads $LCOE_{Resdidential}$ account for the average cost per kWh of useful electricity energy produced by the system to serve residential electric loads only. We divide the annualized costs of producing electricity (notably excluding any cost associated with the potential PUE loads) by the total electric load served.

$$LCOE_{Residential} = \frac{(TAC - \mathrm{TAC}_{\mathrm{asset}} * \frac{Electricity_{PUE}}{Electricity_{Residential}} - TAC_{PUE})}{Electricity_{Residential}} \quad (2)$$

With $\mathrm{TAC}_{\mathrm{asset}}$as total annualized costs of a specific energy system asset (i.e., PV, battery) and TAC_{PUE} as the costs of the PUE asset itself and $Electricity_{PUE}$ [kWh/yr], and $Electricity_{Residential}$ as

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total electric power served to residential electric loads[kWh/yr]. Notably, as we assume simultaneously developing the energy system for residential load and PUE load, we include the costs for the PUE in the calculations, keeping an approach to optimize the entire energy system without taking a specific perspective (see Section 4.1 for a related discussion of alternative calculation methods). Vice versa, we compute the levelized costs of electricity for service of the PUE ($LCOE_{Service}$) accounting for the costs and energy share associated with the PUE load.

Notably, to calculate the share of costs of the PUE sub-system and residential electricity supply sub-system respectively (analogous for $LCOE_{Service}$ and $LCOE_{residential}$) we take an objective technical perspective, sharing the costs of installation and use of the total system based on share of energy consumption (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. While this technical approach is useful to evaluate the performance of the entire system it may differ from an approach taken by current off-grid system operators to calculate tariffs; see Section 4.1 for a related discussion.

3. Results

The following section first describes significant influencers of residential electricity consumption. Subsequently, the techno-economic results of fitting PUE into community consumption patterns are provided.

3.1. Influencers of Electricity Consumption

We observe the time-dependent evolution and variation of electricity consumption patterns (subsection 3.1.1) and time-independent variation of consumption patterns based on socio-economic characteristics (subsection 3.1.2).

3.1.1. Time-Dependent Influences of Electricity Consumption

We study the evolution of electricity consumption across 107 residential electricity users over three years (earliest data log: 10.02.2018; latest data log: 01.12.2021). It is important to note that the applied payment scheme foresees optional (daily, weekly, or monthly) prepayments, in which the user can choose between different credit options reflecting daily power and energy limits. When exceeding the daily energy limit, the user is remotely cut off and connected again when credits are left the next day. When exceeding the power limits, the user is cut off only shortly and reconnected if the power load is reduced. Hence, the studied electricity consumption patterns can be constrained by the tariff chosen and credit management of the household and may not reflect an unconstrained evolution. **Table *3*** presents the evolution of the average energy and power consumption per capita. Whereas the maximum average power demand per household remained more stable over the years, the average daily energy demand increased significantly. While a granular analysis confirms that the average energy demand of connected households increases over time, we also observed that more recently connected households tend to have higher average energy demands than clients connected several years ago (see also Figure A4 of the Appendix). This is explained by an increasing set of available DC appliances offered to local residents, and higher share of high consuming public lights integrated in the nanogrids.

Table 3. Evolution of the daily average energy consumption and peak power load per household.

Year	Average daily household electricity consumption [Wh]	Annual change of average daily electricity consumption [%]	Average daily maximum household power demand [W]	Annual change of maximum average power consumption [%]
2018	8.16	-	2.26	-
2019	21.88	168.27	2.25	-0.75
2020	35.47	62.11	2.27	0.92
2021	50.62	42.72	2.99	32.11

Studying the average monthly energy consumption and peak load per household reveals a seasonal variation of electricity consumption, see **Figure *4***. Both significantly increase after the rainy season (January – April). This is explained by the seasonality of crops, potentially increased liquidity of the households during these months, and less hours of sunshine.

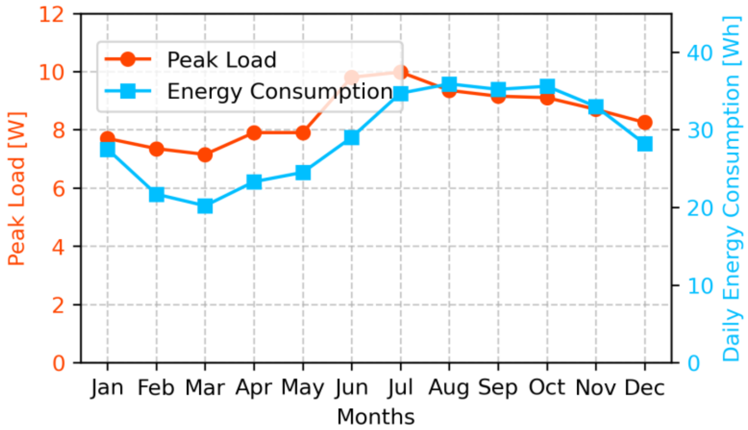

Figure 4. Seasonal variation of the average maximum peak power demand per household and average daily electricity consumption.

3.1.2. Socio-Economic Predictors of Electricity Consumption

Based on the cluster analysis (see Section 2.1), we identify three distinct representative annual electricity residential consumption profiles (silhouette score s = 0.53). **Figure 5** illustrates the average daily load profile of each household of the sample group within the distinct clusters, with the aggregated average load profile of all households belonging to a cluster highlighted in bold. Cluster 0, including 17% of the residential sample group, exhibits a significant evening peak demand, peaking at 15W around 8 pm, accompanied by a baseload demand of approximately 3 W throughout the rest of the day. Due to its comparatively high demand (ca. 40 Wh per day), we label the profile as "high-consumption". The majority (66%) of residentials belong to Cluster 1 – "low-consumption" – in which we observe minimal daytime consumption, with a low night demand of around 1 W and a small evening peak of about 4 W. Cluster 2 – "nighttime consumption"- (17%) displays a moderate-sized evening peak of 10 W, a night consumption around 8 W, and no daytime consumption. Within these profiles, two extremes emerge: a low-demand consumer in Cluster 1, characterized by a consumption not exceeding 4 W and consistently lower than other groups, and a high-demand consumer in Cluster 0, with an evening peak demand four times higher than the low demand consumer and twice that of Cluster 2. Throughout the day, the high demand profile maintains the highest overall demand, dominated by a nearly constant medium baseload at 3 W.

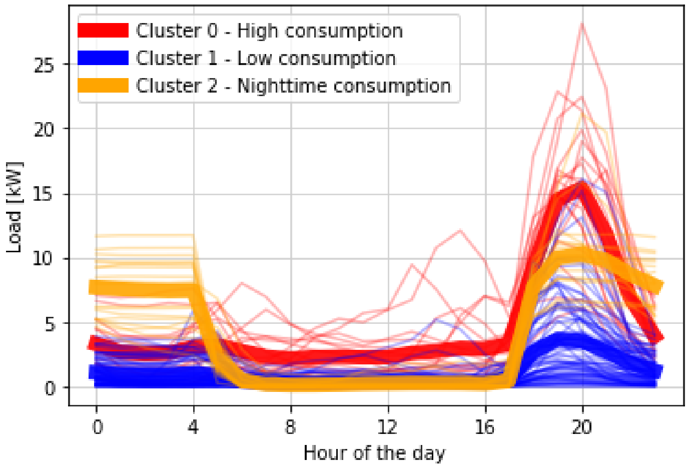

Figure 5. Representative daily electricity consumption profile of each household in a cluster and the average cluster profile, highlighted in bold.

Based on the series of Chi-square and Fisher tests, we detect a significant correlation between socioeconomic characteristics and cluster membership of residents in the community. **Table *4*** presents the socio-economic and demographic variables detected as significant to predict a distinct cluster membership (for an overview of the statistical analysis results, see Table A2. of the Appendix). Based on the results, we can characterize the distinct clusters and use the variables to predict a particular energy consumption pattern. For instance, a high share of "Eco" tariffs within the sample group significantly predicts a Cluster 1 membership – expressing a low load consumption load profile. Similarly, the public lighting tariff predicts the membership to a high consumption Cluster 2. While predicting energy consumption behavior based on tariffs is trivial, we find other more complex correlations. For instance, we see a high share of residents working as traders, which significantly correlates with an electricity consumption profile as reflected in Cluster 0, with a high peak during the evening. Most of the samples included in the low-consumption profile (Cluster 1) instead are stated they are farmers (47%). Cluster 0 households also report the highest number of LED bulbs (2.2). In addition, the presence of a phone charger (83%) and 12V plugs (56%) correlate with the membership in Cluster 0. LED spot ownership, however, predicts the membership to Cluster 2.

Table 4. Socio-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**		**Chi2**	**df**	**Fisher Exact**	**p-value**	**Cramer´s V**
		C	**EC**	**C**	**EC**	**C**	**EC**					
Tariff Groups												
Eco	Yes	0	5.7	33	22.6	1	5.7	21.172	2		<0,001	0.445
	No	18	12.3	38	48.4	17	12.3					
Eclairage Plus	Yes	9	4.7	17	18.6	2	4.7	7.585	2	6.98	0.025	0.275
	No	9	13.3	54	52.4	16	13.3					

Multimedia	Yes	7	2	4	8	1	2.2	16.654	2	12.37	0.001	0.395
	No	11	16	67	63	17	16					
Public Lighting	Yes	0	2	1	8	11	2	54.137	2	37.199	<0,001	0.711
	No	18	16	70	63	7	16					
Tariff Switch	Yes	11	5	17	19.9	2	5	12.9	2		0.002	0.347
	No	7	13	52	51.1	16	13					
Appliances Ownership												
Led Bulb	Yes	16	14.1	61	55.7	7	14.1	20.201	2	16.635	<0,001	0.435
	No	2	3.9	10	15.3	11	3.9					
Led Spot	Yes	0	2	1	8	11	2	54.137	2	37.199	<0,001	0.711
	No	18	16	70	63	7	16					
USB Phone Charger	Yes	15	8.9	31	35.2	7	8.9	10.021	2	10.199	0.006	0.306
	No	3	9.1	40	35.8	11	9.1					
12V Plug	Yes	10	5.7	21	22.6	3	5.7	6.749	2		0.034	0.251
	No	8	12.3	50	48.4	15	12.3					
LED Bulb Quantity	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					
	8	1	0.2	0	0.7	0	0.2					
Demographic variables												
Number of children*	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				
	4	1	0.6	2	2.2	0	0.3				
Job Groups											
Trader	Yes	9	5.4	17	14.8	0	5.8	13.263	2		0.001	0.429
	No	6	9.6	24	26.2	16	10.2					
Employee*	Yes	4	1.7	4	4.6	0	1.8	5.751	2	4.959	0.056	0.283
	No	11	13.3	37	36.4	16	14.2					
Public Lighting	Yes	0	2.5	1	6.8	11	2.7	40.226	2	31.89	<0,001	0.747
	No	15	12.5	40	34.2	5	13.3					

3.2. Techno-Economic Evaluation of PUE

According to the findings of the statistical analysis in the previous section, we establish scenarios to compare the integration of PUE in residential energy systems with different compositions of residential consumption patterns as explained in Subsection 2.1.3. Hence, we match four PUE integration scenarios with five distinct residential load profile sets, each composing five households posing the average daily load profile of a certain cluster (see **Figure 5**). With this, we can derive valuable information on the fit of a PUE in specific residential energy systems, reflecting residents' distinct socioeconomic and demographic characteristics.

The residential load profile sets are labeled as

- “*Representative demand*”: five residential loads, including three Cluster 1 loads (“low-consumption”) as the most common cluster, one Cluster 0 load (“high-consumption), and one Cluster 2 load (“nighttime consumption”). This set reflects the overall percentage distribution of all samples. Annual residential demand: 101 kWh.
- “*Low demand*”: five residential loads of Cluster 1 (“low-consumption”). Annual residential demand: 43 kWh.
- “*High demand*”: five residential loads of Cluster 0 (“high consumption”). Annual residential demand: 202 kWh.
- “*Low demand with nighttime load*”: four residential loads of Cluster 1 (“low-consumption”) and one load with Cluster 2 profile representing a nighttime load (public lighting). Annual residential demand: 70 kWh.
- “*High demand with nighttime load*”: four residential loads of Cluster 0 (“high consumption”) and one load with Cluster 2 profile representing a nighttime load (public lighting). Annual residential demand: 196 kWh.

We evaluate the integration of PUE within the different compositing residential energy systems on technical metrics in **Figure 6** - taking the example of a representative residential electricity

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consumption patterns (see **Table A3** of the Appendix for all scenarios and compositions) and economic metrics in **Figure 7**.

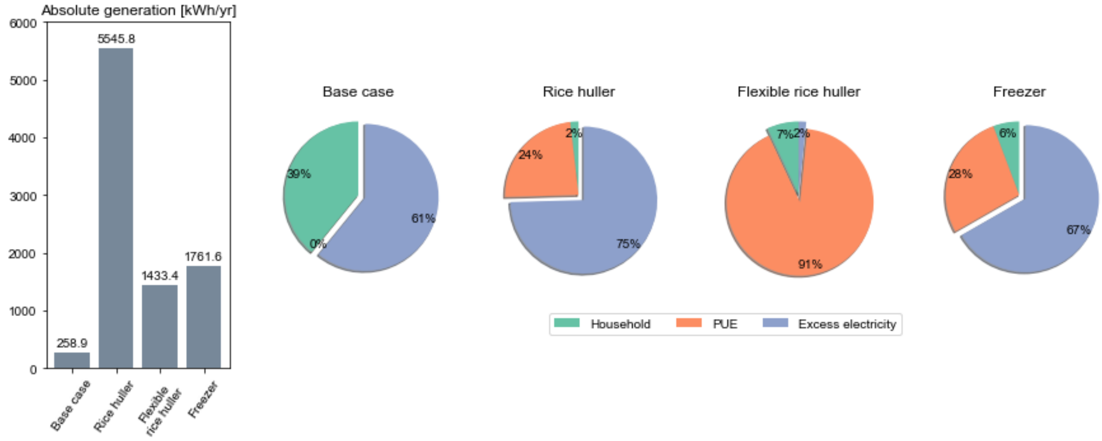

Figure 6. Annual energy generation (kWh/yr) (left) and share of energy consumption of residential loads, PUE loads, and excess generation across the different PUE integration scenarios for the example of the representative demand residential load profile set.

For interpreting the economic results illustrated in **Figure 7** we may compare

i) the difference of $LCOS$within one PUE integration scenario across the different residential load profile sets to understand the suitability of the specific PUE for different communities

ii) the difference of $LCOS$ across different PUE integration scenarios within one specific residential load profile set to understand the best fitting PUE for the respective socio-economic character of the community

iii) the distribution of $LCOS$, $LCOE_{Resdidential}$ and $LCOE_{Service}$ within each combination of PUE integration and residential cluster composition to understand the share of costs associated with supplying electricity to the residential users or the PUE appliance.

Below, we highlight some of the key results derivable from **Figure 7** per PUE integration scenario:

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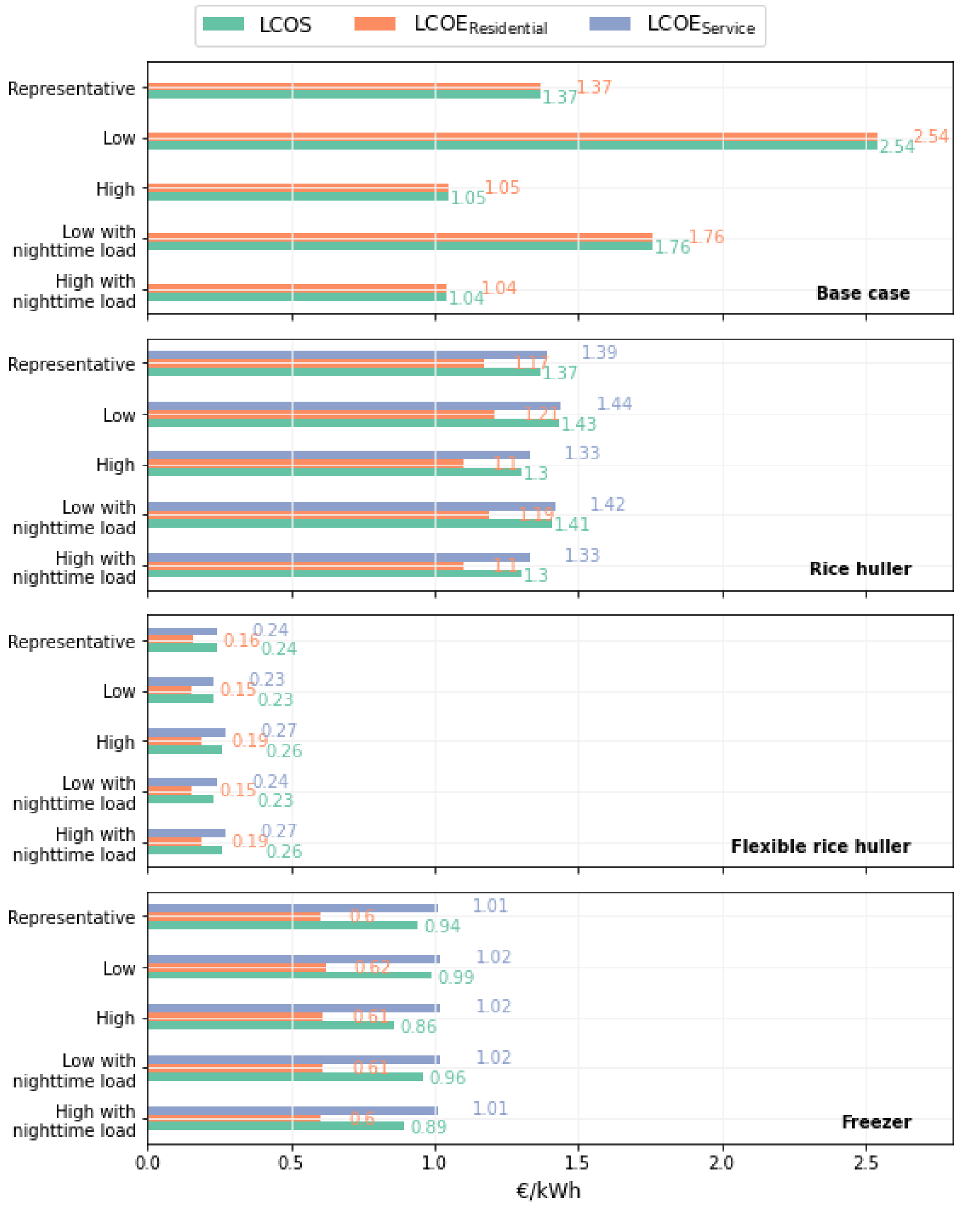

Figure 7. Economic results of the PUE integration scenarios across the different residential load composition sets.

Scenario: Base case residential nanogrid: Supplying only residential loads, the optimized energy system considering a *representative demand* residential load profile set consists of 160 Wp PV and 560 Wh battery storage. The costs of the system are dominated by battery storage (43% of the TAC); see **Figure** *8*. Considering a *low demand* profile set characteristic for a community significantly consisting of residents subscribing for the “Eco tariff” and characterized by owning only a few appliances (light bulbs) with a high share of farmers results in lower total system costs (110 €/yr. vs. 205 €/yr.). However, the relative costs of supplying electricity compared to an opposed *high demand* consumption expected in communities with a significantly increased share of traders, many change-in-tariffs towards multimedia tariff, and many LED bulbs identified are higher. This tendency can increase when considering public lighting as a nighttime load (*high demand with nighttime load*) to be included in the residential energy system with relatively high demand.

Scenario: Integrated rice huller: Integrating a DC rice huller following current consumption patterns of fossil alternatives into a residential energy system increases the TAC of the system by ten times (*high demand* residential load profile set) or up to 20 time (*low demand* residential load profile set). The costs of the rice huller – with an optimized capacity of 1.57 kW_{el} – account for 15% of the total system costs. However, with the PUE load dominating the share of energy consumed in the nanogrid (sixfold the residential consumption in a *high demand* residential load composition set, see **Table A3**), it also dominates the system costs. Hence, the benefits of integrating the rice huller towards reducing the $LCOS$ depend on the residential load composition set, reflecting a different socio-economic and demographic community composition. With the rice huller relatively increasing the costs of electricity production (as seen by the $LCOE_{Service}$ exceeding the $LCOE_{Resdidential}$ under any residential load composition set), we observe increasing $LCOS$ when including a rice huller in a *high demand* load profile composition set – while we observe beneficial effects to the $LCOS$ when increasing the utilization of *low demand* residential load compositions. With splitting the costs across residential and PUE via energy shares (see Section 2.1), the $LCOE_{Resdidential}$ may decrease by 1.35 €/kWh (see a related discussion on cost distribution in Section 4). However, we must therefore carefully note that the integration of PUE can actually result in higher cost for residential electricity consumption (based on the applied calculation of electricity cost), if the two load profiles conflict.

Scenario: Integrated flexible rice huller: Assuming the DC rice huller to have total 'operational freedom' and only requiring a minimum throughput within one year is an unrealistic extreme (assuming abundant rice resources, and ubiquitous storage opportunities). However, some increased flexibility in the operation – ergo, some changes in the usage patterns of the asset users compared to current usage patterns of fossil counterparts – can arguably be expected to a certain degree to facilitate operational constraints imposed by the DC system (see Section 4 for a related discussion). Comparing the results with the ones of the constrained rice huller scenario shows the significant cost reduction achievable when increasing the flexibility of PUEs, which is unlocked by shifting the load of the PUE towards the peak PV irradiation hours with least conflicting residential loads; thus, avoiding costly energy storage (see Figure A2 for a representative load profile). The required power of the PUE asset is reduced to 0.6 kW_{el} (compared to 1.57 kW_{el}). Further, the additional amount of PV and battery to be installed is reduced compared to a residential system to satisfy the PUE load. While for example, in a *representative demand* residential household composition set, the optimal size and associated share of TAC of the PV and battery exclusively feeding residential loads are 160 Wp and 0.56 kWh, the size and costs (see **Figure** *8*) increase to 3.43 kWp (20% of the TAC), and 13.28 kWh (60% of the TAC) respectively when integrating a DC rice huller following the load profile of fossil alternatives currently used (*scenario: integrated rice huller)*. However, when maximizing the flexibility of the huller (*scenario: integrated flexible rice huller)*, the required PV size increases to ca. 900 Wp compared to the residential system, while the battery size remains the same compared to feeding only residential loads. Hence, significant battery costs can be saved when increasing the flexibility of the PUE to be operated at peak irradiation times. Consequentially, with the amount of energy consumed in the nanogrid being dominated by the rice huller (see **Table A3**), achieving low costs of supplying the rice huller with electricity due to its operation harnessing excess electricity of the residential grid only, the $LCOS$ can be reduced to less than 0.3€/kWh. Significantly, by smoothening the load curve in low-demand consumption scenarios, increasing the total system utilization, and reducing the excess electricity share (see **Table A3**), the cost-efficiency measures are improved compared to a *high demand* residential load profile set (see **Figure 7**).

Scenario: Integrated freezer: Integrating a freezer into the energy system quadruples the TAC of the nanogrid when considering a *low demand* residential load composition set of the community (552 €/yr. vs. 139€/yr.) and triples the costs assuming a *high demand* residential community set (607 €/yr. vs. 205€/yr.) (see **Figure** *8*). There is only a slight variance in the $LCOE_{Residential}$, suggesting that the applicable consumption composition has little impact on the cost of electricity provision for households. The comparison of the *base case residential nanogrid* only feeding residential loads and the *integrated freezer* scenarios reveals that through the integration of the freezer, the $LCOE_{Residential}$ can be reduced substantially. For the *low demand* residential load composition set, the $LCOE_{Residential}$ are reduced by 75% and for the high demand consumption composition the $LCOE_{Residential}$ are reduced by 43%. Compared to the *integrated rice huller*, the PV and battery optimized capacity and share of costs of the TAC are 1.1 kWp (23% of TAC) and 1.84 kWh (31% of TAC) – the latter of which is a sixth

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of the capacity required to satisfy the rice huller. Notably, the freezer device (150 W) constitutes a third of the TAC (198€/yr), see **Figure** *8*.

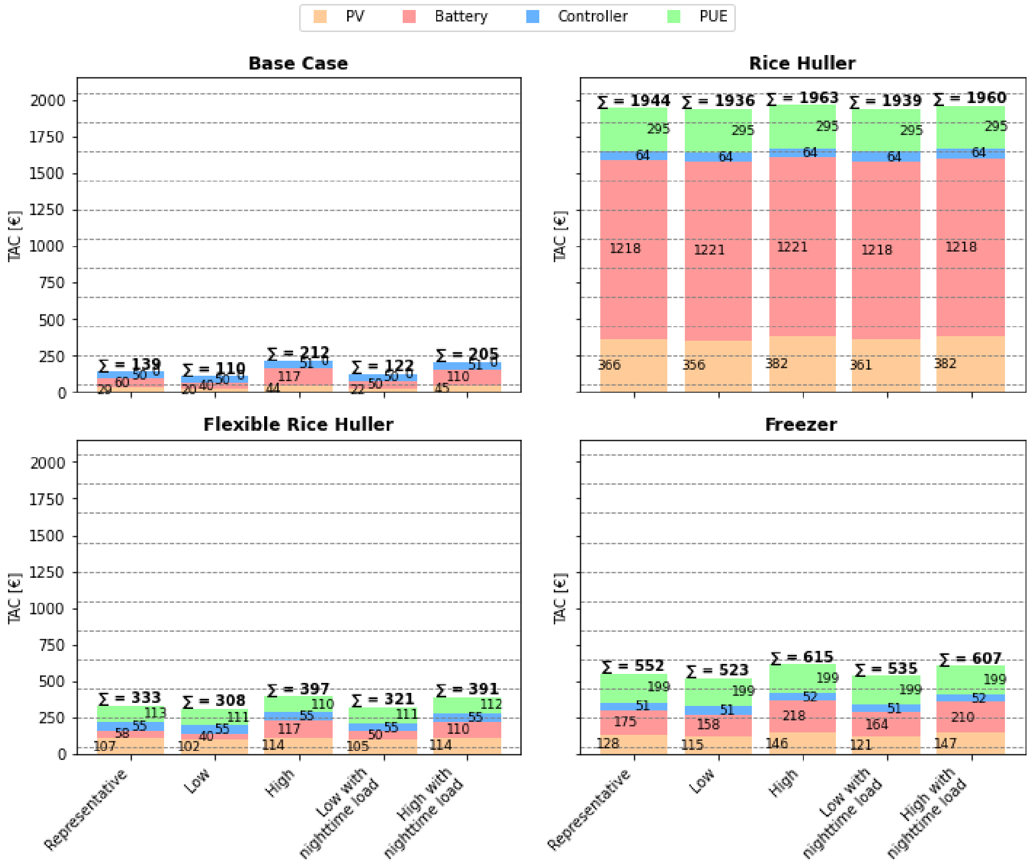

Figure 8. Share of energy system asset costs of total annualized costs for the different residential load profile sets and PUE integration scenarios.

4. Discussion

In this section we first critically reflect on the limitations of our analysis, discuss the impact of the limitations on the results, and outline alternative pathways and approaches to follow-up on in future work (Section 4.1). Subsequently, we present and discuss the implications of our study results (Section 4.2). Lastly, we consider impacts of PUE integration on local value streams of communities (Section 4.3).

4.1. Critical Reflection on the Study

Our investigation was motivated by the potential to enhance off-grid electrification by systematically integrating residential and PUE loads in early energy system planning. PUE are seen as a potential driver for facilitating local value creation in rural communities. Integrating PUE in residential off-grid systems is challenging, as the electricity consumption profile of the PUE must not conflict with residential consumption patterns of the community. Thus, residential consumption patterns must be known – a condition often not met due to a lack of data and complex data acquisition. We suggest a methodology to overcome this barrier by identifying socio-economic and demographic predictors for residential electricity consumption patterns, which are easily accessible via survey. We developed and tested our methodology by relying on data accessible from the operations of a local company providing nanogrids to residential customers in northern Madagascar. The available data had been acquired for a different purpose. It's utilization as part of this study is a secondary application. Because the scope and content of the data was not specifically tailored to serve the use of this study, it lacked relevant accuracy and constituted limitations, especially regarding the selection of available socio-economic and demographic variables. For instance, these variables neglected some common socio-economic characteristics that often are reported to influence energy-related decisions, such as the educational level (e.g., [47]). This limits the explorable potential determinants of energy consumption patterns. Future studies should meticulously design and tailor socio-economic and demographic data collection to the analysis's purpose.

Further, the uncertainty in constructing estimated load profiles for PUE assets, which we derived from user (or users of the currently used fossil counterpart) descriptions assessed via interviews, highlights the need for closer monitoring of user behaviour and preferences to usage patterns when implementing DC-based PUE alternatives. For instance, we derived the load curve for a rice huller based on interviews conducted with current users of diesel-based rice hullers. While we relied on the user´s descriptions of usage patterns, including the start and the duration of operating hours, closely monitoring users' daily routines would be required to reconstruct a valid daily load profile. In addition, participatory workshops can be conducted to gain a more accurate understanding of the degree of flexibility in the operational preferences of users of PUE assets. This is especially to be considered when substituting current fossil-based PUE by renewable powered alternatives (as suggested in the *integrated rice huller scenario* of our analysis), as the degree of flexibility of the asset itself, and the usage preferences of PUE users may differ compared to the fossil counterpart. It is important to note that to fully understand the potential for an adaptive PUE operation, one must also consider the product and value flows associated with a PUE asset.

Our economic calculations included PUE asset costs in the TAC and cost-efficiency measures ($LCOS$ and $LCOE_{Service}$). This approach was chosen for the following reasons: First, there are significant (financial) barriers for the local community members to purchase DC PUE assets. Thus, arguably, the PUE assets should be supplied as part of the system infrastructure otherwise it would be unlikely that the asset can be financed by a single potential asset operator. Second, the perspective taken holds the view of designing optimal energy systems. Reflecting on the complex interrelation and roles within the community and energy system (see ***Figure 1***) we are explicitly not considering the perspective of the energy system operator (who operates the energy system and only sells electricity). As underpinned by our study, the energy system is designed and tailored to one specific PUE – hence it is not reasonable to strictly separate the energy generation from the PUE operation, but the PUE asset and energy system are inherently linked. In fact, a PUE operator may not even be free to decide what asset to connect to the system, as this may be constrained by the energy system in place. This observation underlines the imperative need for the co-design of energy systems to maximize the value creation of all parties involved and to ensure the energy system design is tailored to serve prioritized needs.

To increase local relevance of system planning analyses, locally applicable circumstances need to be integrated as design choices, as was done in our study with the deliberate design regarding gate PUE asset financing. However, to understand the implications of a study, it is important to understand the underlying respective design choices and perspectives. Generalized analyses that go beyond the scope of the case study of this paper may consider not including PUE asset costs as system costs, assuming residential user ownership. This can significantly lower the costs of providing electricity. However, with our approach of calculating the costs of delivering electricity to residents and the PUE service respectively by splitting the costs of energy system assets among the two loads based on the share of energy consumed, the cost-efficiency measures would be equal, with the costs of providing electricity to the PUE significantly lowered compared to the current calculation method (e.g., in scenario of and *integrated freezer* a *representative* household load composition set the $LCOE_{Service}$ would be reduced from 1.01 €/kWh to 0.6 €/kWh). Hence, one could argue that the costs of providing electricity to the PUE load in our calculation may be overestimated. A detailed investigation of the share of energy system costs would require studying the actual utilization of energy system assets (e.g., battery storage) to satisfy each load (this could, e.g., be integrated via considering the time of use of assets).

Alternatively, energy system planners may choose to evaluate the integration of PUE based on only the additional costs caused by the integration compared to an energy system that only serves

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residential loads; quasi ex-post. To illustrate this consideration, we use the example of an *integrated freezer* in a residential nanogrid with a *representative* load profile set. The residential system's TAC and $LCOS$– posing the $LCOE_{Residential}$ – are only 138 €/yr and 1.37 €/kWh, respectively. Integrating the freezer increases the system TAC to 553 €/yr or 353 €/yr when including or excluding the PUE asset. Splitting the costs as suggested by our technically neutral calculation, $LCOE_{Service}$ and $LCOE_{Residential}$ amount 0.94€/kWh respectively and 0.6€/kWh respectively when including the PUE, or 0.6€/kWh each when neglecting the costs for the freezer (notably, substantially reducing the relative costs of electricity supply). However, when only accounting for the additional energy system costs (PV, battery) caused by the integration of the freezer compared to the residential system, we may only consider 414 €/yr (including PUE investment costs) or 215 €/yr (excluding PUE investment costs) as additional TAC accountable for the service provision. The respective calculated $LCOE_{Service}$ are 0.85 €/kWh and 0.44 €/kWh – lower than calculated via our technically neutral approach – while the $LCOE_{Residential}$ would remain at 1.37€/kWh. This example very well shows the impact the different calculation methods may have when energy planners use cost-efficiency measures as a benchmark for setting tariffs.

By using the calculation approach as in our study, we implicitly offer a novelty for energy system planners to provide a particular service rather than electricity only – which would crucially align with the rationale of PUE integration in energy systems (see Section 1). While our analysis still compares the energy systems based on the costs per unit of energy (kWh), we suggest following the approach of comparing energy systems based on the services delivered. However, this may significantly increase the complexity of evaluating the costs and end products. For example, the product "hulling rice" comprises various components, e.g., energy system costs, operating and maintenance costs, service commission, etc. Hence, a close look into the entire value chain is required rather than separately evaluating individual components. This is only possible for services that already exist locally.

The stated calculation examples and the subsequent discussion of implication showcase the importance of understanding the rationale of energy system planning for a given context. Assumptions for energy system planning should be formulated in collaboration with the local community to increase the relevance.

4.2. Implications of the Key Findings

This study shows that integrating PUE can reduce the costs of residential energy provision. However, for individuals, the costs of PUE assets may pose a significant barrier to it's uptake. In the case of a DC freezer, one interviewee, whose family owns a DC freezer, reported paying off the microcredit over a duration of 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 (we may approximate a fictive tariff with the $LCOE_{Service}$ to approximately 38,000 AR per week (ca. 8€)). The owner reports daily profits after paying bills of 5000 AR (ca. 1€) from selling a broad spectrum of goods, including iced water, ice for cooling food and beverages, and frozen juice. While the economic benefits for the PUE owner are thus evident, our analysis shows potential for other community members to gain financial benefits from the integration of PUEs when assuming different stacked tariffs are in place. We observed the difference in $LCOE_{Residential}$ and $LCOE_{Service}$, during the analysis. Notably, the LCOE only reflects a part of the costs to be included when determining a tariff but may be seen as indicative for the tariff to be set. From our analysis, we can observe that the $LCOE_{residential}$ (significantly) decreases when integrating the PUE (*integrated freezer*), while the $LCOE_{Service}$, exceed the $LCOE_{Residential}$. To illustrate the consequences, we conduct a very simplified thought experiment. Considering a *low demand* residential composition set, 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 five *low demand* loads, and one freezer integrated into the system, the operator of which is charged a tariff in the magnitude of the $LCOE_{Service}$,. Adopting the new $LCOE_{Residential}$ found within the analysis for integrating a freezer ($LCOE_{Residential}$= ca. 0.6€/kWh), the

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annual costs of electricity to pay for each household are reduced by 74 percent to approximately 6.5 €, while the costs for operating the freezer would total to 533€ per year. While this calculation is a simplification, it 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 the literature [15] that the entire local economy may be improved when overcoming initial barriers to investing in the PUE to be integrated into the system. However, one must carefully note that we also reported the exact opposite and increasing $LCOE_{Residential}$ when PUE and residential load consumption patterns conflict, causing additional energy system costs (*integrated rice huller* in a *high demand* residential load composition set).

Our study highlights the importance of matching the electricity consumption patterns of the residential community and the PUE to minimize the costs of electricity production. The associated cost of electricity production varies significantly between the different scenarios and underlying household load composition sets considered in this case study. **Figure *9*** shows the $LCOS$ and the respective excess electricity percentage share for every scenario and residential load profile composition set considered in this study. Significant deviations in the associated cost of supplying electricity can be observed for both different residential consumption composition, when considering a single selected PUE asset, which is indicated by a uniform colour code but different marker in **Figure *9*** and between different PUE assets, which are represented in different colours. The high variance among electricity generation costs underlines the potentials that arises from a 'match making' approach, as proposed in this study. The spread of costs within a specific PUE integration scenario across the different residential load composition sets can be interpreted as 'robustness' of the PUE load curve towards potentially conflicting residential load profiles. The results indicate that the robustness of the associated electricity provision cost can be increased when comparing non-integrated and integrated systems. The maximum spread of $LCOS$ in the *base case* scenarios is 1.5 €/kWh – whereas it is only 0.13 €/kWh for the *integrated freezer* scenario and the *integrated rice huller* scenario. The economic impact of integrating a rice huller into a residential energy system in *flexible rice huller* scenario is even less sensitive towards the load profiles of the residentials than a freezer with a spread of only 0.02 €/kWh. This expresses that integrating a PUE in a residential off-gid energy system decreases the sensitivity of the economic results (measured by $LCOS$) towards underlying residential community electricity consumption patterns.

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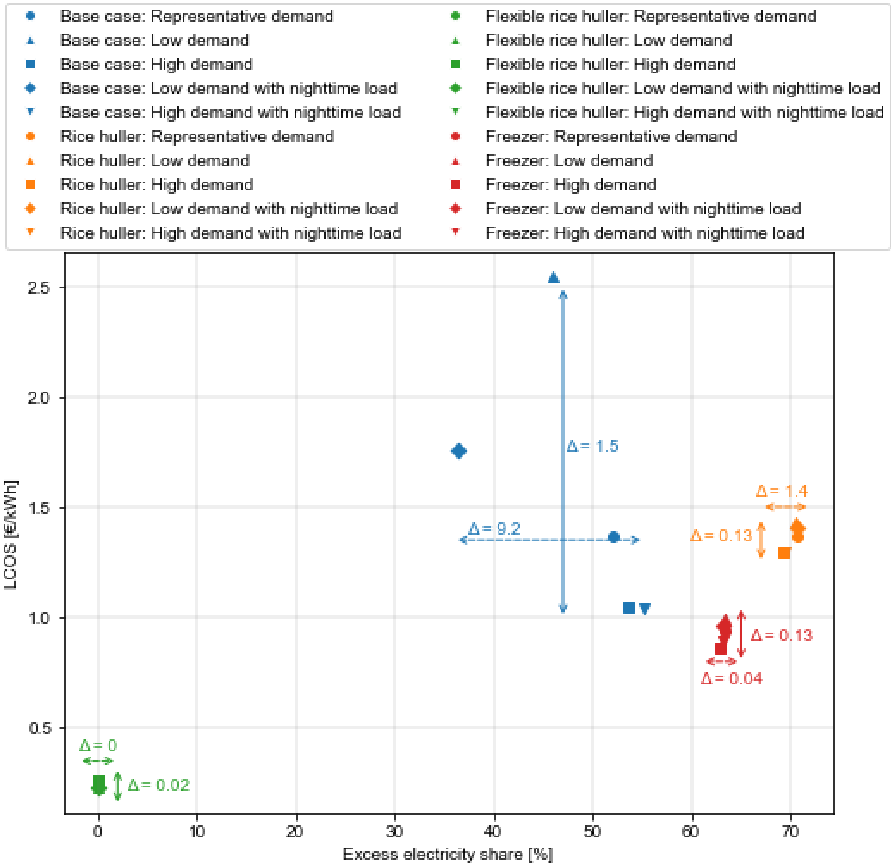

Figure 9. LCOS and percentage share of excess electricity for scenarios considered in the relevant case study.

The proposed matchmaking approach necessitates information regarding the locally relevant PUE and the associated operational behaviour. In our study we propose an approach using survey data and statistical analysis to identify consumption determinants and calculate representative consumption profiles. Provided sufficient data can be collected to ensure a high degree of informative value, the identified determinants can be an efficient short-cut in identifying favourable locations of integrated energy systems. Further statistical verification may expand the area of application to a broader geographical scope, beyond the surveyed region. The appropriate selection of PUE for a given location ultimately requires close collaboration with the community that the energy system serves. The identification of existing value streams, the selection of relevant PUE and through understanding of operational preferences, which can be achieved through KIIs, is a key requirement for the efficient integration of households and PUE loads. The long-term success of a deployed energy system is substantially influenced by the accuracy of the assumptions made regarding the energy-related needs in the community while planning the energy system. To improve the accuracy and to increase the overall value of the energy system, it is essential to include the community in energy system planning. We explored the potential of adapted operational behavior for PUE. To showcase the impact on electricity provision cost, we defined a PUE asset integration case in which its operation did not collide with residential patterns and to harness peak PV irradiation. In line with current literature (e.g., [21]), our study underscores the substantial impact of increasing the operational flexibility of PUEs on decreasing energy system costs. This is reflected in the fundamental differences in the percentage share of excess electricity when comparing the rice huller and the flexible rice huller in **Figure 9**. While the assumed operational adaptation is not realistically achievable, it showcases the theoretical potential that exists. The actual operational preferences and willingness to adapt can only be determined in close collaboration with the PUE operator and may be linked to further product and value streams within the community. To even extend the importance of community participation

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in energy system planning and a productive, democratic, and constant exchange between energy system investor and it´s users, we may consider the earlier (see Chapter 1) mentioned risk of the PUE associated business failure being earlier than the payback of the energy system. Such financial risks may be mitigated when constantly being in exchange with the user of the energy system and providing supportive measures where relevant.

4.3. Considerations on PUE Impact on Value Streams of the Community and its Environment

Our results highlight the crucial importance of including the local community in the decision making and energy system design processes. First, energy system planners must identify a PUE asset that is relevant to address the service needs of the community to ensure a sustained uptake of the service, and electricity consumption. Hence, a close interaction with the community members is inevitable. Second, identifying preferences in and the degree of flexibility of usage patterns of PUE users can support aligning the PUE load profile with residential load profiles, which is critical to minimize the costs of electricity supply (see Section 3.2). In the qualitative data acquisition and in our analysis, we focused on the local community directly interacting with the energy system. These considerations offer new insights into more relevant and more efficient designs of off-grid energy system. However, we recommend that future studies further systematically integrate considerations regarding the external environment, in which the community is set. The interaction of the community with the external environment further improves the information value of the conducted analysis in several ways. First, the potential for a flexible operation of the PUE asset is constrained by the product and value streams of local markets. Second, the identification of relevant service needs (see Section 2.1.2) is linked to services that may exist outside the scope of the community. Third, the impact of introducing PUE assets, in terms of development, may have implications beyond the community, as it will change existing value and product streams.

To showcase the relevance of integrating considerations regarding the environment in which the community is set, in the following, we discuss potential implications. The results of our economic analysis (see Section3.2) suggest that the integration of PUE can improve the economics of off-grid energy systems. As suggested in our discussion, these benefits could further be distributed to residential energy system users. Additionally, we provided evidence of potential improved household income (Section 4.2) when investing in PUE. It is important to note that in this analysis we only consider improved household income via potential savings of energy expenditures. A detailed description of additional income generated by the PUE products is laid out in a report of the associated ENERGICA project [31]. However, we must keep in mind that the integration of PUEs impacts the energy system operator and the PUE user and may disrupt the local value stream patterns of the community and its external environment. 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 [15,48]. Riva et al. [17] show the complex causal loops associated with energy access and productive activities. Based on interviews with several community members in our case study, we can simplified illustrate changes in the local community value changes when for example, considering the uptake of a freezer in a village (**Figure *10***). A corresponding description for the case of an electrical rice huller is documented in the associated ENERGICA project [31].

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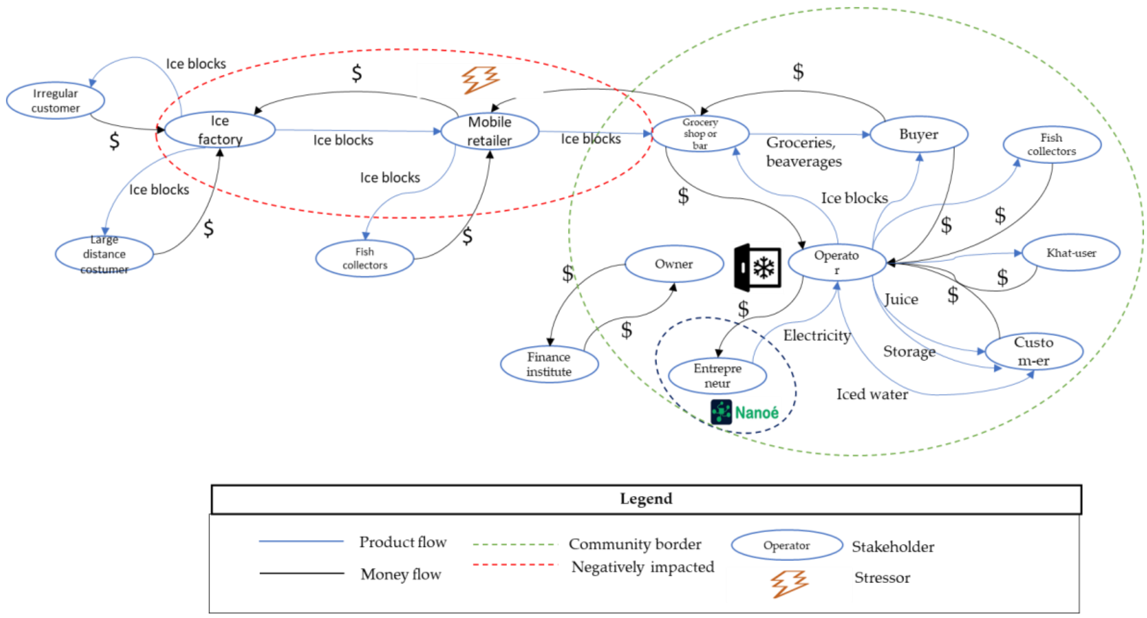

Figure 10. Simplified schematic representation of community value flows when adopting a freezer in a village. For an analogous description of changes in community dynamics for electrified rice processing machine see [31].

Figure *10* depicts the systems and value streams of the environment associated with the product 'ice' that is anticipated in a scenario that introduces decentralized ice production via a nanogrid-connected freezer. The value streams that existed prior to the availability of locally produced ice are disrupted. It is expected that ice buyers (i.e., grocery shops and bars) that previously purchased ice from mobile retailers, who are transporting ice from large factories in nearby cities, may now buy ice that is produced locally. Hence, one must note that the introduction of PUE in a decentralized grid and the associated increased local economic activity may lead to other stakeholders experiencing negative consequences (e.g., ice delivery or fuel delivery). Consequently, it is not given per se that all local stakeholders profit from increased uptake of PUE. For the planning of off-grid energy systems, it is therefore relevant to be aware of the entire associated value chains of products and thoroughly establish potential negative consequences. The importance of carefully weighing potential system disruptions is acknowledged in literature. Literature shows that the uptake of PUE may increase inequalities or may have negative impacts the income of some parts of the population. For example, Khandker et al. [49] find comparatively wealthier families that can afford to invest in PUE to increase their income due to PUE usage. In contrast, families that cannot afford a PUE remain comparatively poor. Further, substituting labor-intensive jobs with the PUE appliances threatened the jobs of low-income families. This also applies to eradicating jobs associated with fossil fuels when implementing renewable energy sources, including (i.e. selling candles or kerosene [50]). Prominently, the threat of increasing inequalities associated with PUE applies to gender-based inequalities. Many PUE stimulate activities and professions that either men or women predominantly carry out. Hence, a discrepancy in income stimulation from PUE is evident in the literature [48].

Given the risk of unintended consequences, in particular with regard to reinforcing local inequalities, the type of employment should also be evaluated to determine whether a certain PUE actually contributes to livelihood improvements [51]. In addition, Terrapon-Paff et al. [48] highlight including dedicated activities to raising awareness amongst stakeholders across the entire value chain to prevent from causing inequalities when implementing PUE.

5. Conclusions

Our study proposes a novel methodology to identify PUE that fit into community structures and off-grid residential energy systems, improving the (financial) sustainability of rural electrification projects and the efficiency of energy system planning. In contrast to current methods, our approach has the potential to avoid extensive data collection and overcome data gaps.

Our key findings emphasize the significance of aligning PUE electricity consumption patterns with residential patterns to minimize electricity production costs. We observe that considering preferences in and the degree of flexibility of usage patterns of PUE users within the energy system design process is crucial to align the different loads, unlock synergies, and finally reduce the LCOE.

We further discuss the financial capacity of community members to invest in PUE assets as a critical determinant of electricity production costs. In our analysis, we explore different perspectives of energy system planning and discuss different ownership and finance models of PUE assets and their impact on the cost distribution of the system - and potential implications for consequential electricity tariffs. This discussion complements the existing literature advocating for strengthening the financial capacity of rural community members to invest in PUE assets. According to our analysis, if the PUE asset is taken over by the investor of the energy system itself, cost distributions are possible (depending on the PUE asset and the structure of the community load patterns), which may increase the total electricity generation costs. Accordingly, a sustainable economic benefit to all parties through the financing of PUE assets as part of the energy system is not unconditional.

In the existing literature, PUEs are essentially justified by the narrative of an anchor load - a reliable and relatively higher demand for electricity and thus a source of income. While this in practice must carefully be reviewed and is not generalizable (i.e., considering short business lifetimes or erratic operation of PUE businesses), our analysis confirms the attributed a plausible potential of the PUE to reducing the financial risk of a project. Provided the PUE operational lifetime matches the economic lifetime of the energy project, and a reliable operational pattern of the PUE asset can be assumed, we observe that the integration of PUE assets in residential community energy system reduces the sensitivity of energy supply costs towards different community energy consumption patterns – and thus offers potential to reduce the financial risk of the project. However, given the preconditions of reliable and sustained electricity off-take by the PUE enterprises, we again highlight the crucial role of offering support and actively engage with the community and PUE users not only during energy system planning, but throughout the project operation.

Our discussion highlights the spectrum of rationales for off-grid energy system planning and the importance of transparency in the energy system planning process and continuous project operation. The locally relevant rationale for energy system planning can only be formulated in a collaborative process involving all locally relevant stakeholders and is influenced by local dependencies, opportunities, community structures, and the external environment in which the community is set. The identified rationale translates into applicable energy system design criteria, businessmodels and ownership models. Future research should develop novel approaches to facilitating the collaborative process, foster co-creation activities in off-grid energy systems planning and harmonize expectations and goals across the actors involved in energy system decision making, including residential community member, PUE user, and energy system operator

Exploring local value streams of the community and it´s environment, we observe the need for energy system planners to address the broader implications of PUE integration, such as its impact on local community value streams and potential unintended consequences, including increased inequalities. In line with the literature, our study underlines that PUE can positively impact the energy system and the local community's economy. However, this is not unconditional, and we must respect that the benefits of PUE are not equally shared among all community stakeholders. We recommend considering the local value stream patterns beyond the community directly impacted by PUE asset integration and include the complex interactions of the community with its surrounding environment to prevent adverse negative effects from PUE integration in rural settings.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix

Table A1. 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

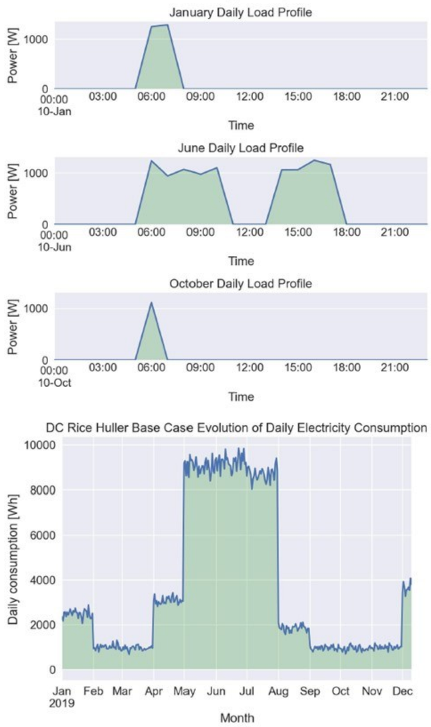

Figure A1. Load profile examples of the electric rice huller.

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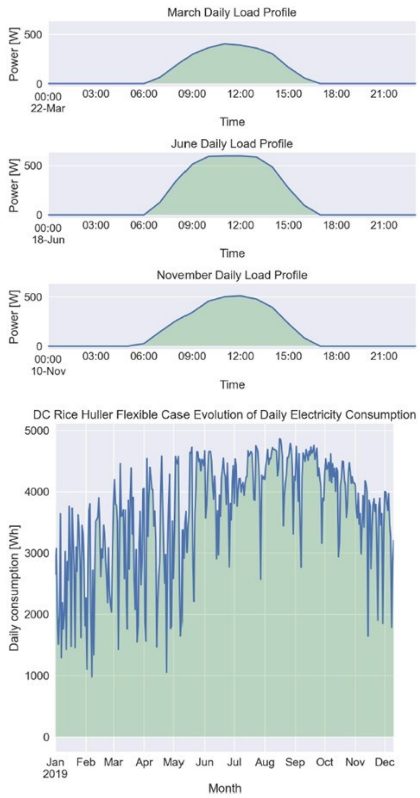

Figure A2. Load profile of the electric rice huller assuming maximum flexibility by only determining a minimum rice production over the entire year. Notably, this scenario poses an unrealistic extreme.

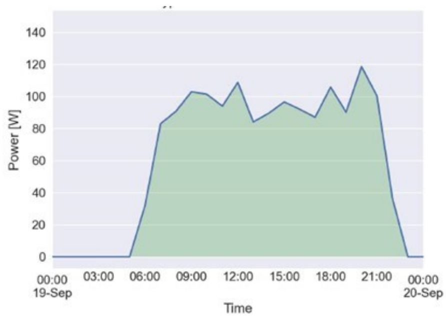

Figure A3. Load profile examples of the electric freezer.

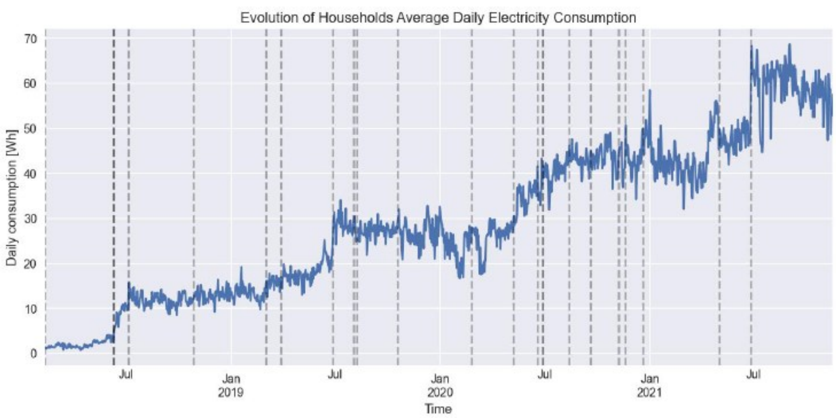

Figure A4. Average daily electricity consumption per household across all nanogrid clients in the case study area. The dashed line indicates commissioning of new nanogrids.

Table A2. Results of the statistical analysis on socio-economic and demographic predictors for energy consumption patterns.

Variables		Cluster 0		Cluster 1		Cluster 2		Chi2	df	Fisher Exact	p	Cramer´s V
		C	EC	C	EC	C	EC					
Tariff Groups												
Eco	Yes	0	5.7	33	22.6	1	5.7	21.172	2		<0,001	0.445
	No	18	12.3	38	48.4	17	12.3					
Eclairage	Yes	6	5.7	23	22.6	5	5.7	0.165	2		0.954	0.047
	No	12	12.3	48	48.4	13	12.3					
Eclairage Plus	Yes	9	4.7	17	18.6	2	4.7	7.585	2	6.98	0.025	0.275
	No	9	13.3	54	52.4	16	13.3					
Multimedia	Yes	7	2	4	8	1	2.2	16.654	2	12.37	0.001	0.395
	No	11	16	67	63	17	16					
Multimedia Plus	Yes	2	1	4	4	0	1	2.099	2	1.827	0.392	0.144
	No	16	17	67	67	18	17					
Public Lighting	Yes	0	2	1	8	11	2	54.137	2	37.199	<0,001	0.711
	No	18	16	70	63	7	16					
Tariff Switch	Yes	11	5	17	19.9	2	5	12.9	2		0.002	0.347
	No	7	13	52	51.1	16	13					
Appliances Ownership												
Led Bulb	Yes	16	14.1	61	55.7	7	14.1	20.201	2	16.635	<0,001	0.435
	No	2	3.9	10	15.3	11	3.9					
Led Spot	Yes	0	2	1	8	11	2	54.137	2	37.199	<0,001	0.711
	No	18	16	70	63	7	16					
TV	Yes	3	2	8	8	1	2	1.116	2	1.095	0.6	0.102
	No	15	16	63	63	17	16					
USB Phone Charger	Yes	15	8.9	31	35.2	7	8.9	10.021	2	10.199	0.006	0.306
	No	3	9.1	40	35.8	11	9.1					
12V Plug (Simple&Double)	Yes	10	5.7	21	22.6	3	5.7	6.749	2		0.034	0.251
	No	8	12.3	50	48.4	15	12.3					
LED Bulb Quantity	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					
	8	1	0.2	0	0.7	0	0.2					
Survey Variables												

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	free	1	0.2	0	0.7	0	0.1					
Occupant status	owner	14	14.8	54	52.7	5	5.5	5.182	4	5.946	0.195	0.181
	tenant	1	1	3	3.6	1	0.4					
	large	8	4	11	15.2	2	1.8					
House_size	medium	8	10.6	42	39.8	5	4.6	8.515	4	7.027	0.089	0.226
	small	0	1.3	7	5.1	0	0.6					
	0	0	0.2	1	0.7	0	0.1					
	100000	0	2.5	10	8.6	2	0.9					
Monthly household income	150000	7	7	25	24.4	2	2.6	6.689	10	8.661	0.568	0.207
	200000	6	4.5	14	15.8	2	1.7					
	300000	2	1.2	4	4.3	0	0.5					
	500000	1	0.6	2	2.2	0	0.2					
	0	0	1	5	3.6	0	0.4					
	1	1	0.4	1	1.4	0	0.2					
	2	1	3.4	15	12.3	1	1.4					
Nb_household_members	3	8	4.2	13	15.1	0	1.7	16.766	12	14.922	0.149	0.312
	4	3	4	15	14.4	2	1.6					
	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					
	1	1	3	13	10.8	1	1.2					
Nb_adults	2	16	13	43	46.6	6	5.4	4.865	6	4.818	0.608	0.169
	3	0	0.2	1	0.7	0	0.1					
	0	1	2.9	13	10.9	1	1.3					
	1	8	4.6	16	17.4	0	2					
Nb_children	2	3	4.4	19	16.7	1	1.9	16.175	8	13.283	0.065	0.31
	3	3	3.6	11	13.8	5	1.6					
	4	1	0.6	2	2.2	0	0.3					
					Job Groups							
Trader	Yes	9	5.4	17	14.8	0	5.8	13.263	2		0.001	0.429
	No	6	9.6	24	26.2	16	10.2					
Farmer	Yes	8	7.9	25	21.6	5	8.4	4.083	2		0.13	0.238
	No	7	7.1	16	19.4	11	7.6					
Employee	Yes	4	1.7	4	4.6	0	1.8	5.751	2	4.959	0.056	0.283
	No	11	13.3	37	36.4	16	14.2					
Public Lighting	Yes	0	2.5	1	6.8	11	2.7	40.226	2	31.89	<0,001	0.747
	No	15	12.5	40	34.2	5	13.3					
Other	Yes	1	1.7	6	4.6	1	1.8	1.198	2	0.849	0.676	0.129
	No	14	13.3	35	36.4	15	14.2					

Table A3. Technical results of the PUE integration scenarios.

			Representative demand	Low demand	High demand	Low demand with nighttime load	High demand with nighttime load
PUE Integration Scenario	Base case	Residential demand [kWh]	101.24	43.08	201.76	69.51	196.45
		PUE demand [kWh]	0.00	0.00	0.00	0.00	0.00
		Excess electricty share [%]	51.97	46.02	53.64	36.39	55.18
		Excess hours	3433	2804	3474	2670	3575
	Rice huller	Residential demand [kWh]	101.24	43.08	201.76	69.51	196.45
		PUE demand [kWh]	1309.15	1309.15	1309.15	1309.15	1309.15
		Excess electricty share [%]	70.67	70.51	69.28	70.71	69.43
		Excess hours	3142.00	3289.00	3303.00	3236.00	3297.00
	Flexible rice huller	Residential demand [kWh]	101.24	43.08	201.76	69.51	196.45
		PUE demand [kWh]	1309.14	1309.14	1309.14	1309.14	1309.14
		Excess electricty share [%]	0.12	0.12	0.12	0.12	0.12
		Excess hours	137	136	132	132	136
	Freezer	Residential demand [kWh]	101.2	43.1	201.8	69.5	196.4
		PUE demand [kWh]	485.0	485.0	485.0	485.0	485.0
		Excess electricty share [%]	63.3	63.3	62.8	63.2	63.1
		Excess hours	3841	3892	3856	3859	3901

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