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Including greenhouse gas emissions and behavioural responses in the optimal design of PV self-sufficient energy communities

Abstract. Purpose - This paper aims at considering both the greenhouse gas (GHG) emissions and behavioural response in the optimal sizing of solar photovoltaic systems (PV modules and batteries) for energy communities. The objective is to achieve a high self-sufficiency rate whilst taking into account the grid carbon intensity and the Global Warming Potential of system components. **Design/methodology/approach** - Operation and sizing of energy communities leads to optimization problems spanning across multiple time scales. To compute the optimisation in a reasonable time, we first apply a simulation periods reduction using a clustering approach, before solving a linear programming problem. **Findings** - Our results show that the minimum GHG emissions is achieved for self-sufficiency rates of 19% in France and 50% in Germany. **Research limitations/implications** - Our analysis is restricted to specific residential profiles: further work will focus on exploring different types of consumption profiles. **Practical implications** - This paper provides relevant self-sufficiency orders of magnitude for energy communities. **Originality/value** - This article combines various approaches in a single use case: environmental considerations, behavioural response as well as multi-year energy system sizing.

Keywords: Behavioural response, Greenhouse gas emissions, Optimisation, Self-sufficiency, Energy communities, Energy sufficiency, Photovoltaic, Battery storage.

INTRODUCTION

In the current context of climate change, reducing the environmental impact of energy consumption is crucial. In the electricity field, one lever is to deploy renewable energy sources to replace conventional generation. However, the various components of renewable energy systems also induce greenhouse gases (GHG) emissions over their life cycle. In particular, reaching high levels of self-sufficiency may result in oversized systems.

Similarly, with energy communities, there is potential conflict between lowering overall GHG emissions, and increasing self-sufficiency rates. At the same time, the installation of local renewable generation technologies can entail virtuous behavioural response (Luthander et al., 2015).

In this article, we propose an energy modelling methodology considering both behavioural responses and environmental impacts of self-sufficient systems over their entire life cycle. We present the case study of photovoltaic (PV) and storage equipped dwellings, where a compromise has to be made between the reduction of GHG emissions and PV self-sufficiency rate. The aim of this article is twofold:

- Selecting a relevant optimisation method to minimise GHG emissions including behavioural responses to PV self-sufficiency systems.
- Providing quantitative optimisation results on GHG emissions for PV self-sufficiency rates with associated energy system sizing.

The article first presents energy sufficiency and environmental consideration in the modelling of energy communities, before introducing the mathematical formulation for the optimal design of a PV self-sufficient energy community. The data sources and management as well as the obtained results are then detailed. Finally, perspectives and conclusion are offered.

NEW CONSIDERATIONS IN THE MODELLING OF ENERGY COMMUNITIES

Renewable energy communities should play a significant role in the energy transition toward European carbon emission goals. They reflect a growing desire for more sustainable technologies, and local governance (Brummer, 2018). Until recently, they have lacked a clear status in national legislation, however, this is changing as all member states of the European Union are required to have a framework for renewable energy communities in 2021 (Jeriha, 2019).

Energy sufficiency in energy communities

Behavioural responses to the installation of renewable energy systems, and in particular PV systems, has been underlined in various economy (Bauwens and Eyre, 2017) or engineering (Luthander et al., 2015) research works. These suggest that the installation of PV systems could induce energy sufficient behaviours.

Energy sufficiency actions can be defined as “actions which reduce energy demand, to take us towards the energy sufficiency state, whilst at the same time changing the quantity or quality of the energy services demanded in a sustainable way and not below people’s basic needs” (Bierwirth and Thomas, 2019). A growing literature shows that energy-sufficient lifestyles could potentially contribute to GHG emission reductions, yet this potential contribution is rarely exploited relative to the sole reliance on technology (Samadi et al., 2017). Sufficiency measures have been identified as complementary to other energy transition measures such as efficiency, flexibility, and the development of renewable energies to replace carbon sources (Erba and Pagliano, 2021; Ivanova et al., 2020; Samadi et al., 2017).

The environmental impacts of energy self-sufficiency

As incentives push residential buildings towards local renewable energy production, it is important to highlight that every energy source has an intrinsic embodied environmental impact that should not be ignored. In the context of climate change, one of the most relevant and comparable indicator is the global warming potential (GWP), quantified in kilograms of equivalent CO₂ (kgCO₂-eq), taking into account the radiative forcing over a time horizon of the multiple greenhouse gas (GHG) that are harmful to the atmosphere (Stocker and Intergovernmental Panel on Climate Change, 2013).

In the case of PV panels and batteries, the energy mix of the manufacturing plays a huge role on how much GHG is emitted (De Decker, 2015). This and other factors such as the efficiency or lifespan entail GWP of both batteries and PV modules to be uncertain (Gazbour et al., 2018; Peters, 2017). We establish an analogy between economic and environmental costs. On the one hand embodied GHG emissions are referred to as Capital Expenditure (CAPEX). On the other, emissions from consuming power on the grid, which depend on local electricity mix, are

referred to as Operational Expenditure (OPEX). It is expected that, once PV-equipped households start consuming local PV energy, their OPEX is reduced.

Regarding the perimeter of the study, the GHG emissions are calculated from the perspective of a district in order to answer local energy needs. This means that any exported PV electricity is not discounted in the overall GHG balance of the energy community.

MATHEMATICAL FORMULATION

In this section, we provide the mathematical formulation for minimising GHG emissions of a PV self-sufficient energy community at the design stage. Optimisation problems combining operation and sizing lead to formulation spanning across multiple time scales. On the one hand, short term 15 minutes power and energy constraints, on the other long-term investment decisions impacted by slowly ageing components. Bridging between short and long-term time scales is challenging. To tackle this issue, we reduce simulation periods and we keep the optimisation problem linear. In the following mathematical formulation, solar panel size as well as initial and replacement battery capacities are the critical decision variables. Those decision variables are used to minimise the overall grid emissions for a given self-sufficiency.

Although the optimisation problem is linear (Eq. 1 – Eq. 14), we accounted for long terms dynamics such as:

- battery ageing,
- solar panel ageing,
- battery investment decisions taken throughout the optimisation at year 0, 8, and 16,
- self-sufficiency target over the optimisation horizon.

Short terms dynamics include:

- energy balance at the community level,
- sub-hourly greenhouse gas emissions from the grid,
- battery constraints and scheduling.

CAPEX and OPEX with regards to kgCO₂-eq are defined in (Eq. 1).

$$\text{Min. CAPEX} + \sum_y^Y \text{OPEX}(y) \quad (1)$$

Where CAPEX represents emissions from the solar panels and batteries (Eq. 2). Battery emissions are calculated taking into account the number of years a battery is in service in relation to its lifespan. OPEX(y) represents emissions during the operation of the energy community for a year (Eq. 3). Within a year, we consider a set of P periods with M 15 minutes intervals, so time is defined by a year, a period, and a 15 min interval $t = (y, p, m)$. B represents the set of years when the battery capacity can be renewed (i.e., years 0, 8, and 16).

$$\text{CAPEX} = \text{PV}_{\text{GWP}} \times \text{PV}_{\text{capacity}} + \text{Battery}_{\text{GWP}} \times \sum_b^B \left(\text{Battery}_{\text{capacity}}(b) \times \frac{\text{Battery}_{\text{usage}}(b)}{\text{Battery}_{\text{lifetime}}} \right) \quad (2)$$

$$\text{OPEX}(y) = \sum_p^P \lambda(p) \sum_m^M \left(\text{grid}_{\text{import}}(y, p, m) \times \text{grid}_{\text{emissions}}(y, p, m) \right) \quad (3)$$

Where $\lambda(p)$ is the coefficient representing the weight of the the period p within year y . Energy imports from communities are given by $\text{grid}_{\text{import}}$ in kWh, and $\text{grid}_{\text{emissions}}$ represent the emissions related to the use of the grid in kgCO₂-eq/kWh.

$$\text{grid}_{\text{import}}(t) = \alpha(y) \times P_{\text{consumption}}(t) - PV_{\text{capacity}} \times P_{1\text{kWp}}(t) \times PV_{\text{ageing}}(y) + P_{\text{storage}}(t) + P_{\text{export}}(t) \quad (4)$$

$$\text{grid}_{\text{import}}(t) \geq 0 \quad (5)$$

Where $\alpha(y)$ represents the yearly decrease in consumption, referred to as positive feedback (i.e. the behavioural response). PV is also subject to ageing with $PV_{\text{ageing}}(y)$. Further $\text{grid}_{\text{import}}(t)$ is also constrained by self-sufficiency (Eq. 6).

$$\frac{\sum_y \sum_p \sum_m \text{grid}_{\text{import}}(y, p, m)}{\sum_y \sum_p \sum_m \alpha(y) \times P_{\text{consumption}}(y, p, m)} \leq 1 - \tau \quad (6)$$

Where τ represents the self-sufficiency rate over the horizon of the optimisation. On the storage side, $P_{\text{storage}}(t)$ is constrained to model battery charging and discharging (Eq. 7).

$$P_{\text{storage}}(t) = P_{\text{in}}(t) - P_{\text{out}}(t) \quad (7)$$

$$0 \leq P_{\text{in}}(t) \leq \frac{\text{Battery}_{\text{capacity}}(y)}{2} \quad (8)$$

$$0 \leq P_{\text{out}}(t) \leq \frac{\text{Battery}_{\text{capacity}}(y)}{2} \quad (9)$$

$$\text{Battery}_{\text{capacity}}(y) \times 0.2 \leq E(t) \leq \text{Battery}_{\text{capacity}}(y) \quad (10)$$

$$E(t) = E(t-1) + P_{\text{in}}(t)\Delta t \times \eta_{\text{in}} - \frac{P_{\text{out}}(t)\Delta t}{\eta_{\text{out}}} \quad (11)$$

$$E(0) = E(T) \quad (12)$$

Where η_{in} and η_{out} represent charging and discharging efficiency. We assume that initial and final state of charge must be equal. Further, we make the assumption that batteries can fully charge or discharge in 2 hours, thus we set power limits to half of the battery capacity (Eq. 8-9).

The next constraint (Eq. 13) prevents batteries from having CO₂ arbitrage activities beyond the PV production at t (e.g., charging when grid emissions are low and discharging when they are high).

$$P_{\text{in}}(t) \leq PV_{\text{capacity}} \times P_{1\text{kWp}}(t) \times PV_{\text{ageing}}(y) \quad (13)$$

Finally, the last constraint ensures that battery ageing is applied every year $SoH(y)$, except years $b_0 = 0$, $b_1 = 8$, and $b_2 = 16$ from when the optimisation decides to invest in new battery capacities.

$$\begin{cases} \text{Battery}_{\text{capacity}}(y) = SoH(y) \times \text{Battery}_{\text{capacity}}(b_0) \text{ if } y > b_0 \text{ and } y < b_1 \\ \text{Battery}_{\text{capacity}}(y) = SoH(y) \times \text{Battery}_{\text{capacity}}(b_1) \text{ if } y > b_1 \text{ and } y < b_2 \\ \text{Battery}_{\text{capacity}}(y) = SoH(y) \times \text{Battery}_{\text{capacity}}(b_2) \text{ if } y > b_2 \end{cases} \quad (14)$$

RESULTS AND DISCUSSION

Data sources and data management

The entire study abides by open science principles. The open workflow, code and associated sources are shared online in a Jupyter Notebook as supplementary materials to be accessed, used and appropriate. The use case is a grid-connected energy community of 20 households. The aim of the study is to minimise the GHG emissions of the energy system over its entire life cycle for various self-sufficiency rates, through the sizing of PV panels and batteries. The following data sources were employed, with time steps of 15 minutes over a one year horizon:

- Consumption data comes from 20 selected French households from (Quoilin et al., 2016),
- PV production data are determined with PVGIS (Huld et al., 2012). The chosen locations are Grenoble (France) and Berlin (Germany),
- GHG emissions data of the French power grid comes from the French transmission system operator. They have been updated with the IPCC ratios (Schlömer et al., 2014), in order to take into account the life cycle GHG emissions. A similar method has been used for German power grid emissions.

Considering the time step of 15 minutes and the multi-year optimisation utilised in the proposed case study, computation cost is a major issue. To tackle this, we reduce the simulation period. Several methods exist for sequence reduction and can be mainly categorized into Heuristic Methods, Iterative Methods, and Grouping Algorithms (Sayegh, 2020).

For this work, we use a K-Means clustering approach (using Euclidean Distance) as proposed by (Fazlollahi et al., 2014). For the observations to be representative of both weekdays and weekends, an observation size of 7 days is considered. Additionally, a sliding window approach is utilised, resulting in a sample space of 359 observations (weeks).

Three approaches (the elbow method, silhouette score method (Yuan and Yang, 2019), and the Calinski-Harabasz method (Wang and Xu, 2019)) are considered for the selection of the number of clusters (K-value), that is to say the number of representative weeks to be used in the optimisation. Table 1 below shows the methods considered and the recommended number of clusters for both the French and German use cases.

Table 1: recommended k-value from different methods for the given datasets

	Cluster size (France)	Cluster size (Germany)
Elbow method	11	8
Silhouette score method	2	3
Calinski-Harabasz method	2	2

A K-value of 5 is selected to ensure that the clusters represent at least a majority of the four seasons. This value is also consistent with the average cluster size across the different methods shown in Table 1. Table 2 is a summary of the selected observations, with their corresponding weight (i.e. λ in Eq. 3).

Table 2: Selected observations with their corresponding weights

	France		Germany	
	Period	Weights	Period	Weights
Observation 1	31st Jan– 6th Feb.	10.72	12th – 18th April	9.13
Observation 2	22nd –28th Feb	11.88	8th – 14th July	7.10
Observation 3	28th April– 4th May	5.5	10th – 16th Aug.	14.19
Observation 4	23rd – 29th May.	12.02	11th – 17th Dec.	11.01
Observation 5	1st – 7th Nov.	11.8	24th – 30th Dec	10.57

To validate the design choices, the reduced simulation period data is compared to the results calculated for the complete dataset. Deviations of 0.15% and 5% are obtained respectively for France and Germany. The observations in Figure 1 show the clustering results from the French data.

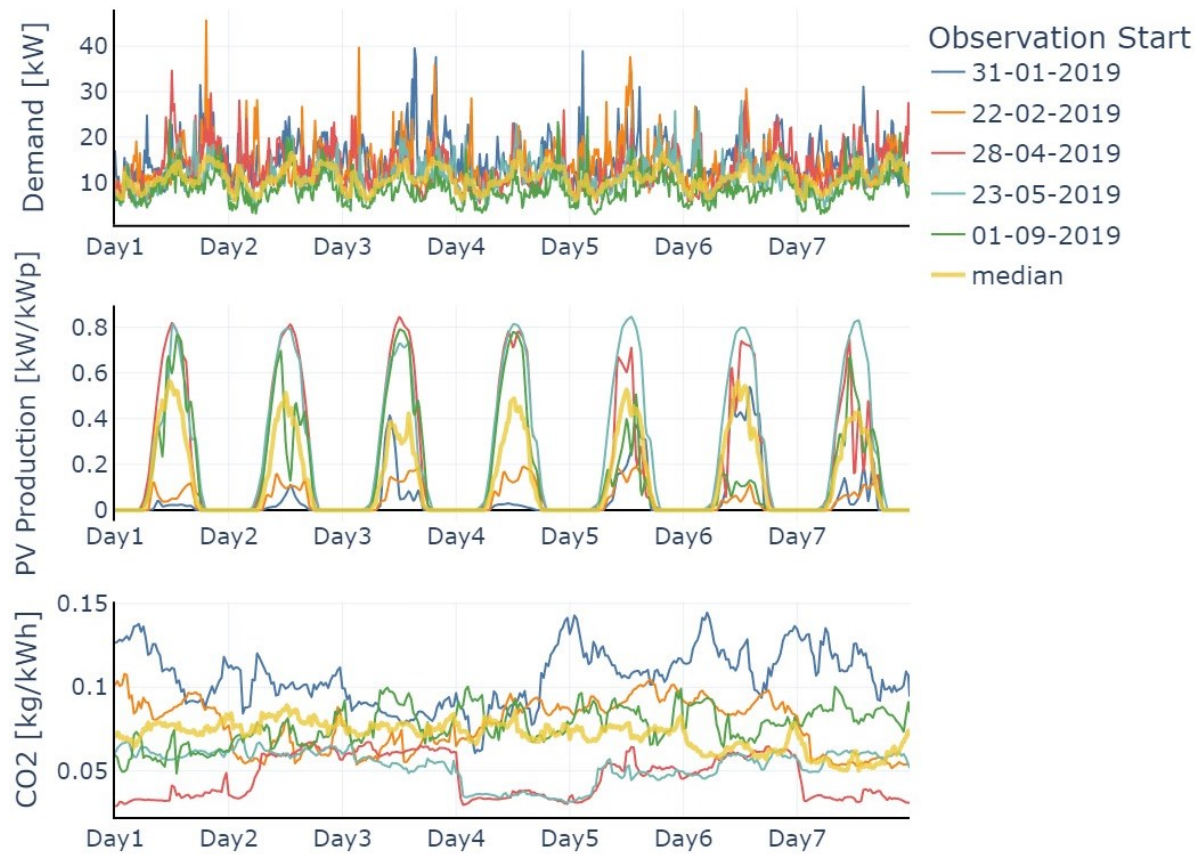


Figure 1: Clustering results for France

Given the high uncertainties on PV panels GWP values, the results will be presented with minimal, median and maximal GWP values. The minimal, median and maximal GWP of PV panels (respectively 858, 1040 and 1240 kgCO₂-eq/kWp) come from the INCER-ACV project (ADEME, 2021). The GWP of the Li-ion batteries is considered equal to 158 kgCO₂-eq/kWh of battery capacity, considering LFP technology. Associated lifespan of 8 years is approximated, considering one cycle per day (Peters, 2017). The maximal Depth of Discharge (DoD) is considered equal to 80%.

Finally, assumptions of energy sufficiency are based on thermal and appliances consumption in the Global North from the Low Energy Demand scenario (Grubler et al., 2018), with an annual decrease of 3% over a 20-years horizon. It is one of the most ambitious scenario regarding energy sufficiency, and thus represents a best case scenario. The reference case consists in no change in the energy consumption, enabling intuitive comparisons.

Results

The study is carried out with the Gurobi solver (Gurobi Optimization, LLC, 2021) for a period of 20 years, including batteries replacements, and provides the following results.

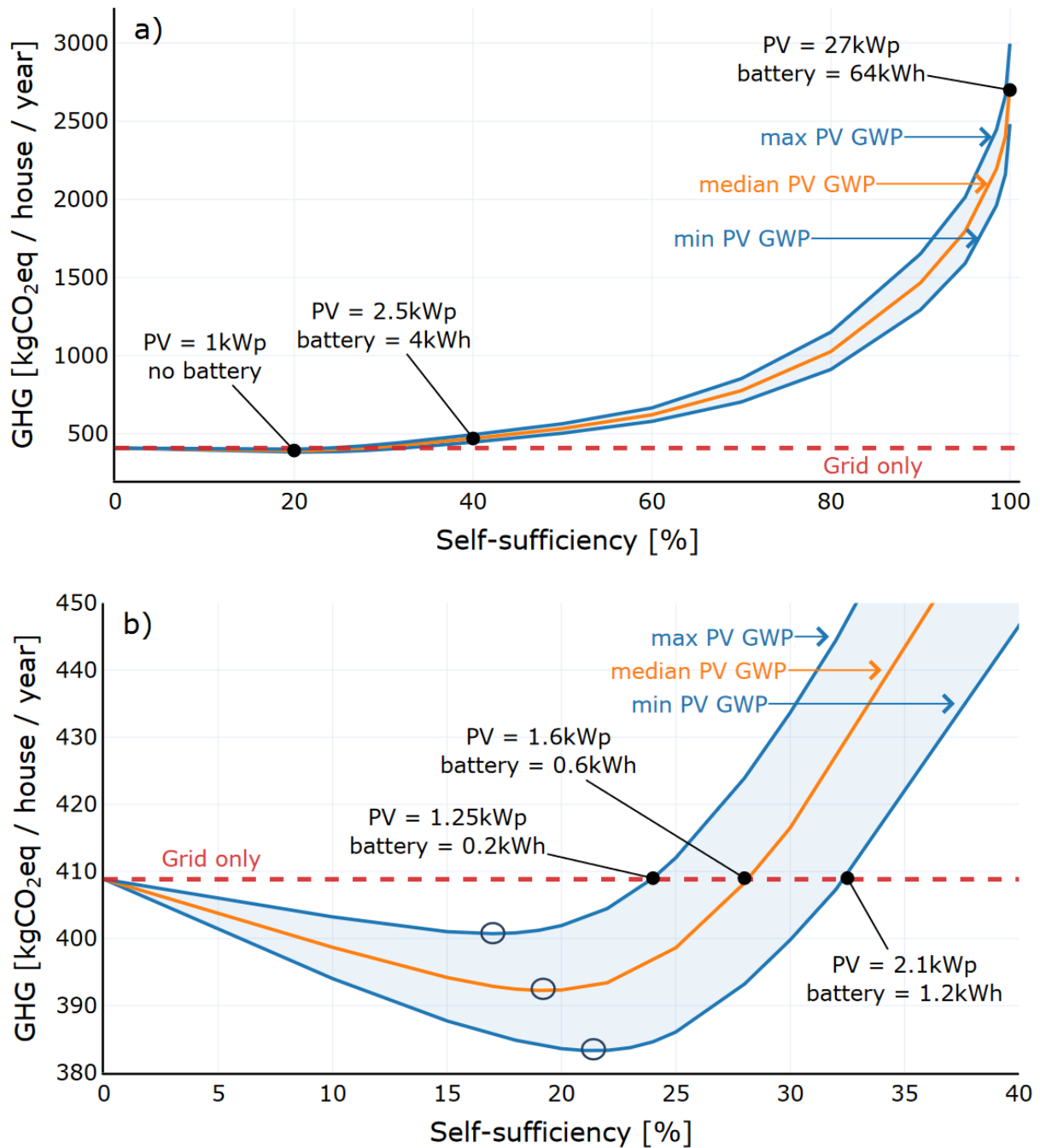


Figure 2: Yearly greenhouse gas emissions of the energy consumption of a household in France as a function of self-sufficiency rates for minimal, median and maximal PV panels GWP, with associated batteries and PV sizing (a), zoomed in between 0 and 40% of self-sufficiency (b).

Figures 2 a and b present the GHG emissions of the energy system per household and per year as a function of self-sufficiency rates in France. On the Figure 2.a, the GHG emissions are soaring after a 40% self-sufficiency rate, which makes associated sizing irrelevant with regards to sustainable energy systems. Figure 2.b present results zoomed in from 0% to 40% of self-sufficiency. A “grid only” threshold was drawn in order to indicate the point where the GHG emissions from grid only would be exceeded. This threshold is exceeded at 24%, 28% and 32% of

self-sufficiency while the minimum GHG emissions value is reached at 17%, 19% and 21% respectively for maximal, median and minimal PV GWP.

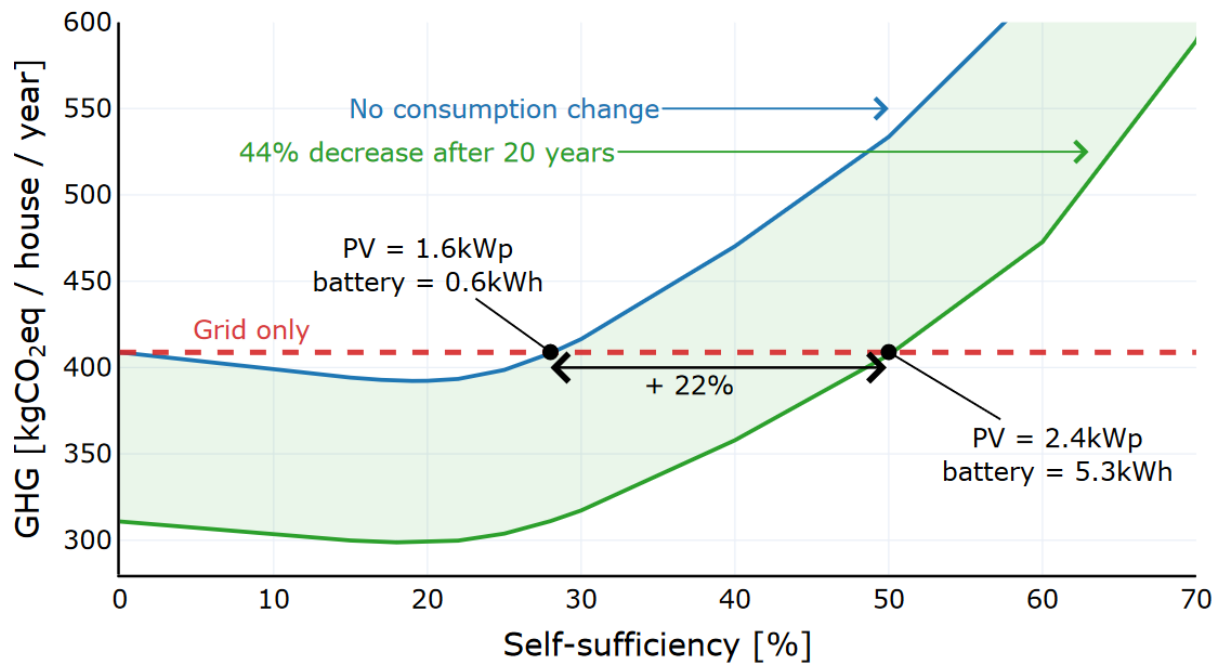


Figure 3: Greenhouse gas emissions of the energy consumption of a household in France as a function of self-sufficiency rates from 0% to 70% with and without positive feedback assumption

Figure 3 presents the results for median PV GWP with the reference and positive feedback scenarios. As expected, we observe that the positive feedback enable to reduce the GHG emissions for a given self-sufficiency rate. This comes from the reduction of the consumption and associated emissions from the grid on the one hand, and sizing of the PV and battery system on the other hand. In the reference scenario, the “grid only” threshold is crossed for battery capacities as low as 0.6kWh. In the positive feedback scenario, higher battery capacities can be installed before the threshold is crossed, enabling a 22% increase of the self-sufficiency rate. At this point, the PV and battery sizing per house is respectively 2.4 kWp and 5.3 kWh, which corresponds to common values for self-sufficiency installations.

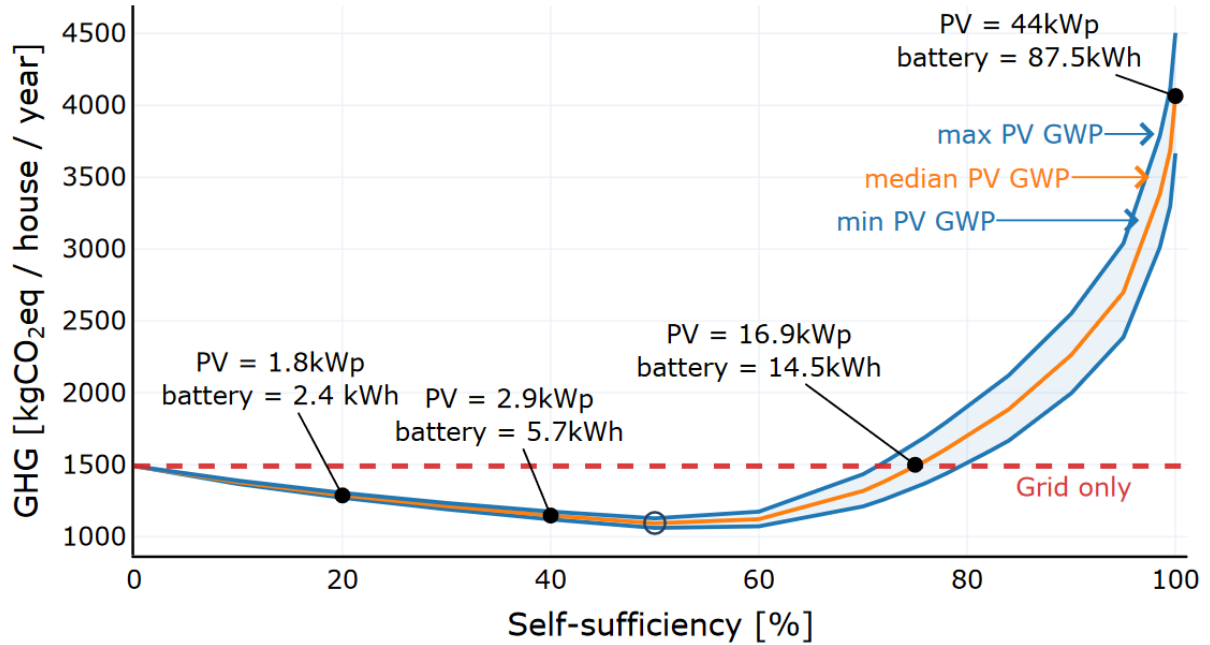


Figure 4: Greenhouse gas emissions of the energy consumption of a household as a function of self-sufficiency rates in Germany for minimal, median and maximal panels GWP

Figure 4 corresponds to Figure 2 results with German grid emissions. Where the French y-axis values starts at 400 kgCO₂-eq per house per year, the German case starts at 1000 kgCO₂-eq due to significantly higher grid emissions than in the French case. A point of attention the authors would like to underline is that the German case presents bigger PV and batteries sizing than the French case for given self-sufficiency rates. This is due to batteries performing arbitrage, which is profitable in Germany since the difference between the minimal and maximal GHG emissions from the power grid is 429 gCO₂-eq/kWh, while it is 166 gCO₂-eq/kWh in France. Figure 4 presents interesting results with a minimum of GHG emissions at 50% of self-sufficiency, and a crossing of the grid only threshold with an already large energy system including 16.9 kWp of PV and 14.5 kWh of batteries for 74% of self-sufficiency in the median PV GWP case.

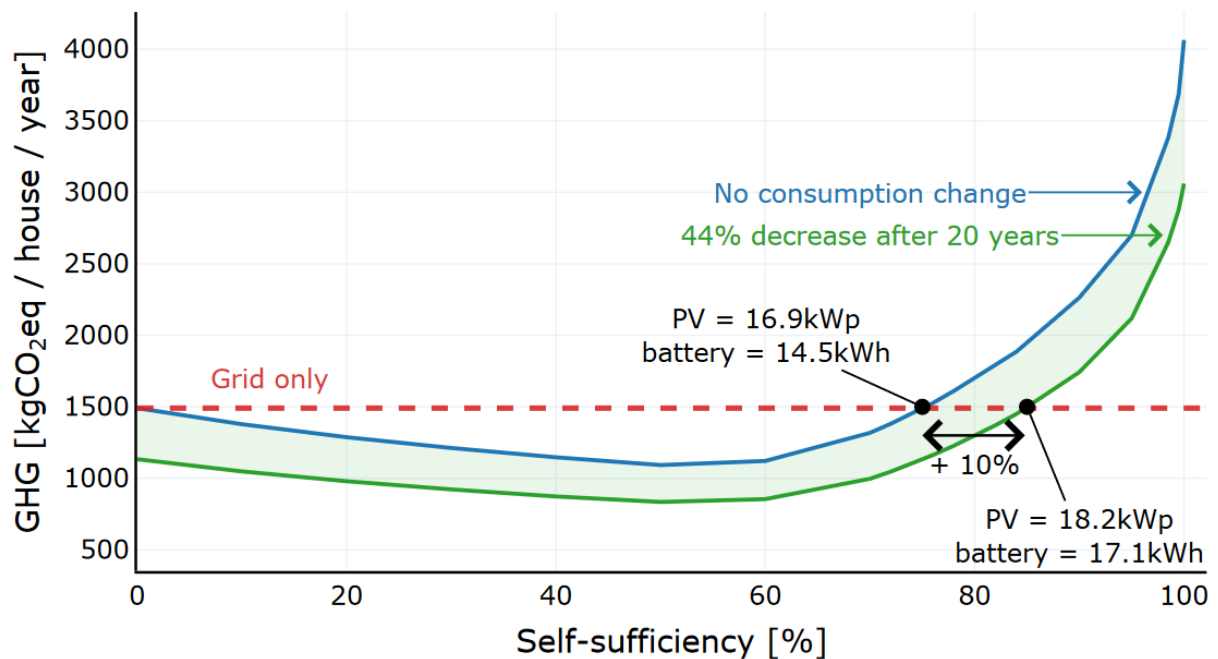


Figure 5: Greenhouse gas emissions of the energy consumption of a household as a function of self-sufficiency rates in Germany with and without positive feedback assumption

Figure 5 corresponds to Figure 3 in the German case, showing the self-sufficiency rates for median PV GWP and both reference and positive feedback scenarios. Once again, we observe that the positive feedback enable to reduce the GHG emissions for a given self-sufficiency rate. The “grid only” threshold is crossed for 10 percent self-sufficiency more in the positive feedback scenario compared to the reference. Finally, for a full self-sufficient district (100%), we can observe a significant GHG emissions reduction with energy sufficiency actions.

PERSPECTIVES

In addition to energy sufficiency, flexibility and in particular demand side management could improve the results in terms of self-sufficiency at constant GHG emissions. Correlation between PV production and consumption profiles, as well as the consideration of a variety of profiles will be explored in future work. Further, aggregated energy sufficiency effects were taken into account in the analysis and could be refined based on the emerging literature. A direct perspective for this work consists in the refined modelling and assumptions for the batteries. This includes considering various cases for parameters such as the GWP or lifespan, including better battery operational management and the use of second hand batteries in the design. Refined assumptions for the evolution of energy mix and reference energy consumption should also be explored.

Finally, the study perimeter brings about many perspectives, with the consideration of:

- other energy vectors such as thermal energy,
- other indicators, such as different environmental impacts, self-consumption, and economic indicator to include the economic feasibility of the systems,
- other countries in the results,

CONCLUSION

In this article, we provide a method to find the optimal sizing with regards to GHG emissions for solar panels plus storage systems to achieve a given self-sufficiency. This method is applied to energy communities whose energy supply is moving from total reliance on the grid to full self-sufficiency. We show that environmental impacts and energy sufficiency potentials should and could be included in energy modelling. The article intends to present a method and trends rather than an answer on GHG emissions for local energy communities. The results show high dependency on GWP data and location for power grid emissions. These results can be used as indicative thresholds in the design of self-sufficient energy systems with comparable residential loads. One can question the environmental benefits of designs reaching self-sufficiency rates higher than 32% in France and 80% in Germany. The code and data are openly available to be adapted to different scenarios. Future work will explore the sensitivity of the results to different load profiles.

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