newTRENDs

Modeling of prosumagers and energy communities in energy demand models

Deliverable D5.2

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Datasets and parts of the energy demand models, which are newly developed within this project, will be made open access latest at the end of the project and can then be found at https://github.com/H2020-newTRENDs. All previously existing datasets and model parts are explicitly excluded from this open access strategy.

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Executive Summary

To achieve the Paris Agreement goals, all countries need to implement two central strategies: i) enhancing energy efficiency (EE) and (ii) decarbonizing the remaining energy supply and demand. Scenarios with different focuses and assumptions have been derived to map this development until 2050. In this context, the newTRENDs project prepares the analytical basis for a "2050 Energy Efficiency Vision" by considering New Societal Trends in energy demand modeling.

- First, in WP2, we identify the new societal trends and their clusters that are expected to be most relevant or disruptive to the future energy demand. The identification is made based on a comprehensive scanning of existing studies and a series of expert workshops. In the end, 14 major trend clusters are identified. Furthermore, for each cluster, we also develop the narrative to describe the potential mechanisms of its controversial impact and disruptiveness for future energy demand.
- Second, in WP3, we take a closer sectoral perspective to review the impact of the new societal trends on energy demand. Four sectors are considered: industry, transport, tertiary and residential. Then, to quantitatively analyze their impact, we also identify the gaps in modeling the new trends in the models involved in the project.
- Third, in WP5-7, we concretely improve and enhance the energy demand models to integrate the new trends. Based on the updated models, we evaluate the impact of the trends on the energy demand in each sector. This is closely related to the policy questions identified in WP4. Furthermore, back in WP3, we also analyze the macroeconomic impacts of the trends.

In this deliverable D5.2, we focus on the modeling of residential buildings and introduce two new models, which were developed in the newTRENDs project: FLEX-Operation and FLEX-Community. They extend our previous modeling suite (INVERT/EE-Lab and FORECAST-Appliance) for the residential buildings to model the new societal trends, e.g., prosumaging and work-from-home. FLEX-Operation calculates the energy consumption and system operation of an individual household or building, including the operation of energy technologies (e.g., battery, PV, heat pump) and load profiles in hourly resolution. Based on the results of FLEX-Operation, FLEX-Community calculates the operation of an energy community from the perspective of an aggregator, who maximizes its profit by (1) facilitating the P2P electricity trading within the community and (2) optimizing the operation of a battery.

Chapter 1 introduces the background of prosumaging and energy community, and reviews the literature on the modeling of individual household and energy community. In Chapter 2, we introduce the development of FLEX-Operation and FLEX-Community in detail, followed by the results of the two models in Chapter 3 and 4. Finally, we conclude in Chapter 5.

The code of FLEX-Operation and FLEX-Community will be available at https://github.com/H2020-newTRENDs by the end of the newTRENDs project.

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1. INTRODUCTION

1.1 Background

With increasing renewable generation integrated into the power system, supply-side fluctuations must be balanced by demand-side flexibility. Therefore, electrification and demand response (DR) are becoming increasingly relevant to the heating transition of buildings, which demands the diffusion of

heat pumps (HPs),
photovoltaic (PV) and energy storage (e.g., battery and hot water tank),
smart energy management systems (SEMSs).

Combining the three technologies is also beneficial from the perspective of an individual household (or building). The household can optimize the heat pump operation to reduce energy costs by saving energy in the tanks or pre-heat the building when the electricity price is lower. Besides, the energy-saving benefit could be further increased with PV and a battery system.

From a market perspective, DR flexibility and PV generation also facilitate the concept of "energy communities". The households in an energy community can trade electricity with each other (peer-to-peer, P2P) within a local micro-grid or even trade with other parts of the country through the national grid, depending on the infrastructure, business model, and policies. In addition, households can also buy the services from an "aggregator", who bundles and manages the flexibility of small consumers and producers and participates in the market activities (Kerscher and Arboleya 2022). In Austria, the revision of the Renewable Energy Expansion Act (Nationalrat 2021) sets the course for renewable energy communities, which is in line with the RED II[1].

Promoted by the declining costs of technologies and support policies, more and more household "consumers" are expected to become "prosumers" (with PV) and "prosumagers" (adding energy storage and SEMS) (Fereidoon Sioshansi 2019). At the same time, they are expected to join the energy communities. As a result, households' electricity consumption can be changed – both the amount and the shape of the load profile - as well as the consumption of the national building stock.

Against this background, the trends of prosumaging households and energy communities demand the analysis of relevant business models and policy instruments, and also motivate the newTRENDs project. In this Deliverable 5.2, we introduce the modeling development in WP5 of newTRENDs, which focuses on the operation of the individual households (consumers, prosumers and

1 Renewable Energy Recast to 2030 (RED II) [EU. Red II, Directive (EU) 2018/2001 of the European Parliament and of the Council of 11 December 2018 on the promotion of the use of energy from renewable sources. text with EEA relevance.; 2018.].

prosumagers) and the energy community. The framework calculates in hourly resolution and provides the interfaces to integrate results from empirical studies based on smart meter data, for example, the T5.1 of newTRENDs.

1.2 Literature Review

1.2.1 Individual Households Modeling

Generally, the models that calculate (simulate or optimize) the building energy demand fall into two categories.

- Among the first is the sophisticated software that can calculate the space heating and cooling demand of an individual building in detail, including TRNSYS, EnergyPlus, IDA ICE, etc. These models are more precise, but the main drawback is the high computational effort and the high requirement for building information.
- The second includes simplified models where an individual building is modeled as resistances and capacities. These models are referred to as "RC models". They are not as detailed as the first category, but also calculate energy demand at the hourly resolution.

The second category of models is used in this study to evaluate the impact of smart energy management system (SEMS), i.e., the prosumaging behavior of households. Two reasons are decisive for this:

1. Apart from space heating and cooling, the model needs to cover electricity consumption load profiles as well.
2. Due to the simplicity of RC models, the heating and cooling modeling can be combined with electricity consumption, PV, and battery into an optimization framework.

Sperber et al. (2020) compared different RC models and showed that the 5R1C approach (described in the norm (DIN EN ISO 13790:2008)[2] can balance the details of building modeling and computation demand of optimization. Besides, the data requirement of buildings is also lower. At last, the 5R1C approach has been tested and compared to more sophisticated models in various studies (Bruno et al. 2016; Leander Kotzur 2018; Michalak 2014; Müller A. et al. 2014).

Several studies combined the building modeling with other energy consumption (incl. hot water, electric appliance, PV and battery, EV) in an optimization framework. The objectives include the minimization of energy cost (Kandler 2017), maximization of the self-consumption rate of a PV system (Klingler 2018),

[2] DIN EN ISO 13790 has been replaced by ISO 52016-1:2017, which is more detailed and models each building element separately. However, from the modeling perspective, it also demands more detailed building data, and most importantly, leads to higher computational effort in operation optimizing. So, in the newTRENDs project, we work with the previous norm.

and peak reduction (Kippelt 2018). The studies analyzed (1) the operation strategy of the energy storage; (2) the optimal size of a PV plus battery system (Klingler 2018); (3) the potential of load shifting (Emeline Georges et al. 2014); (4) impact of variable electricity price (Yousefi 2020). Haupt (2021) summarized the recent modeling studies and their coverage of the major components, as shown in Table 1.

Table 1 Summary of building modeling practices

Paper	Space heating	Space cooling	Building mass	Hot water	PV and battery	Electric vehicle
Angenendt et al. (2019)	√	-	√	√	√	-
Kippelt (2018)	√	-	-	-	√	√
Yousefi (2020)	√	√	√	-	-	√
Salpakari et al. (2017)	√	√	√	√	√	√
Klingler (2018)	√	-	-	√	√	√
Beer et al. (2016)	√	-	√	√	√	√
Kandler (2017)	√	-	√	√	√	√

As shown in Table 1, the space heating (heat pump) is covered by all the models in the studies, because the interaction between heat pump and PV motivates the modeling of household optimization in hourly resolution. Building mass and hot water is also essential to analyze the impact of PV, battery, and EV in an hourly resolution. Two studies cover space cooling as RC models often overestimate the cooling demand (Müller A. et al. 2014; Michalak 2014). Besides, smart devices (e.g., dishwasher, washing machine and dryer with remote control and automation) are also covered by a few models, but their impacts are limited, as shown in the results in (Kandler 2017).

1.2.2 Energy Community Modeling

Along with households changing from consumers to prosumers/prosumagers, the development of energy communities is also expected to play a more significant role in the energy transition of the building sector since these households are too small to join in the electricity markets individually. The reasons for participating in a community are decreasing energy costs and addressing climate change but also the community spirit (Dóci et al. 2015).

The Renewable Energy Directive defines a "renewable energy community" as a legal entity:

a) which, in accordance with the applicable national law, is based on open and voluntary participation, is autonomous, and is effectively controlled by shareholders or members that are in the proximity of the renewable energy projects that are owned and developed by that legal entity.

b) the shareholders or members of which are natural persons, small and medium enterprises (SMEs) or local authorities, including municipalities.
c) the primary purpose of which is to provide environmental, economic, or social community benefits for its shareholders or members or for the local areas where it operates, rather than financial profits.

An energy community can be controlled by its members based on a general agreement or by an "aggregator". The aggregator (1) shifts loads in the community to internally reduce the imbalance costs in real-time; and (2) controls a group of storages and loads in the day-ahead market (DAM) and in the balancing market to minimize the imbalance costs (Ali et al. 2015). The latest European framework assigns the aggregators a fundamental role in the energy market liberalization and distributed energy resources integration towards carbon-neutral energy systems (Kerscher and Arboleya 2022). Okur et al. (2021) reviewed the business models that an aggregator can implement by trading the flexibility obtained from community participants in different electricity markets.

In the literature, the modeling of energy communities is mostly at a microgrid level (Gruber et al. 2021). Hirschburger and Weidlich (2020) focuses on the P2P trading of PV generation in the community, and different models are used to determine the economic benefits for each community. Koirala et al. (2016) compared different options to integrate energy systems into an energy community (e.g., community micro grids, virtual power plants, energy hubs, prosumer community groups, etc.). Huang et al. (2022) investigated the impact of climate change on the P2P trading performance in energy communities and found that larger households will benefit more than smaller households.

PV systems are of particular interest to energy communities. Given the other possible options, PV systems are the most established (Hirschburger and Weidlich 2020). Fina et al. (2018), Fina et al. (2020), Hirschburger and Weidlich (2020) showed that the self-consumption rate of PV systems can be maximized in a community. This benefits the community members and reduces grid stress. Additionally, with a shared battery, the self-consumption rate can be increased, and the peak demands can be shaved even more (Roberts et al. 2019). Finally, by sharing the investment costs, the risk for individual households to invest in batteries can be reduced. However, the study also suggests that thermal storages (e.g., DHW storage) may be more attractive financially because of the high battery costs.

From the perspective of aggregators, Mahmoudi et al. (2017) analyzed their participation in the DAM and balancing market to minimize the balancing costs. On the other hand, the literature also suggests that the peak shaving potential by energy communities is substantial. As shown by Han et al. (2022), the increased peak demand of an electrified heating network can be substantially reduced by employing an energy community.

Compared with the studies reviewed in Section 1.2.1, the modeling of individual households in the community is significantly simplified to reduce the scale of the optimization. For example, Okur et al. (2021) model the aggregator minimizing the imbalances, in which the loads are classified as non-flexible, semi-flexible, and flexible. No individual households are specifically modeled.

1.2.3 Summary

As reviewed in Section 1.2.1, existing literature models the impact of PV and storage (e.g., battery and hot water tanks) on the energy consumption of individual households. Using RC-models, the heating dynamics of a building can be modeled at an hourly resolution. This significantly supports the analysis of relevant policies promoting the diffusion of heat pumps, PV, batteries, and SEMS.

However, to aggregate the results of individual buildings to the national level, the model has to be flexible to calculate for any representative building (i.e., arbitrary technology configuration) in the stock, which could be a building with a gas boiler and battery but without a PV. Results on aggregation to the national level have already been provided with this model in Mascherbauer et al. (2022).

In Section 1.2.2, one gap is identified in the modeling of energy communities, the linkage between individual households and energy community models, i.e., to construct the energy community with the households calculated in the first model. This provides much more detailed modeling at the building level, especially the heating dynamics of buildings. Furthermore, under different business models of the aggregator, we can evaluate if a representative household would be more likely to stay in or leave the community.

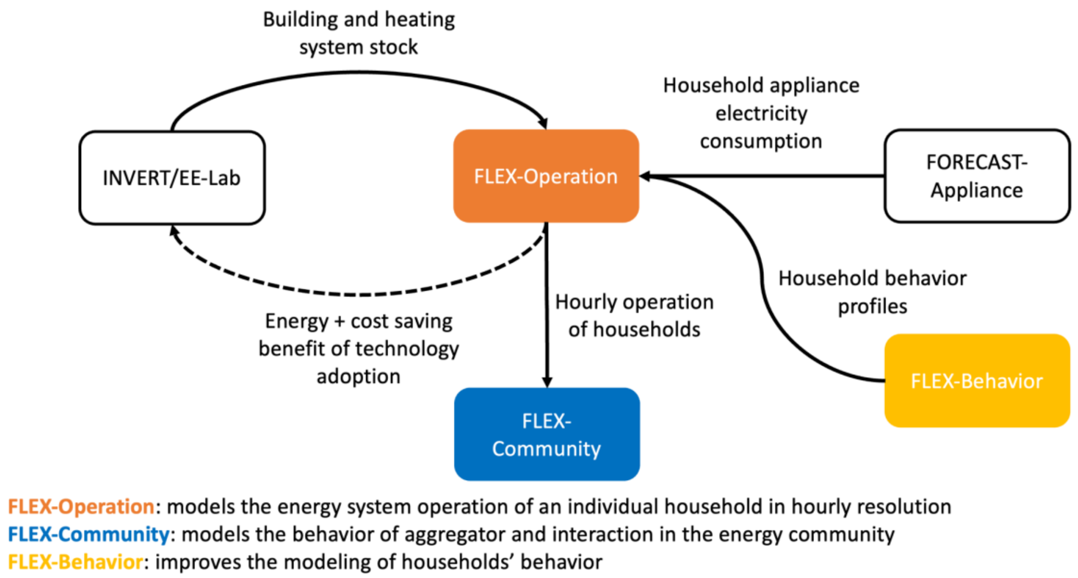
1.3 Motivation and Structure

The motivation of WP5 of newTRENDs is to improve the building modeling suite and to analyze the societal trends of prosumaging and energy communities. As the starting point, INVERT/EE-Lab and FORECAST-Appliance are the two models that can cover the energy consumption of residential buildings. The two models complement each other and cover the total energy consumption of households.

- Invert/EE-Lab is a dynamic bottom-up techno-socio-economic simulation tool that simulates the technology change and energy demand of space heating and hot water in the building sector. It calculates future scenarios with different policy packages and available technology mixes.
- FORECAST-Appliance calculates the energy consumption of households' appliances, including lighting, refrigerator, computer, air-conditioning, etc. Given the bottom-up design, the technology diffusion and energy consumption can be driven by socio-economic drivers (e.g., population, energy prices, policies like eco-design and energy labeling, etc.), techno-economic characteristics (e.g., operation and standby-power, investment costs), user behavior (e.g., operation hours).

However, both INVERT/EE-Lab and FORECAST-Appliance calculate the energy consumption at the annual resolution and cannot model the prosumaging behavior and energy community, which requires an hourly resolution to consider the impact of household behavior, PV generation, and energy storage (thermal and battery) on energy consumption. In this regard, we developed the FLEX-Operation and FLEX-Community models to improve the building modeling suite and support relevant policy analysis.

Figure 1 Building modeling improvement in the newTRENDs project



Source: Own Visualization

As shown in Figure 1, model interaction is summarized below in brief. More details are provided in the following chapters.

1) INVERT/EE-Lab calculates the investment decision (building renovation and heating system investment) in the building stock. The calculation is performed at the representative building level, then aggregated to the national level by multiplying the number of the representative buildings in the stock and summing up the results.
2) FLEX-Operation takes the results of building and technology stock from INVERT/EE-Lab and calculates for each representative building in hourly resolution. The results include operation of technologies (e.g., battery, PV, heat pump, etc.) and households' load profiles. Furthermore, FLEX-Operation can also provide implications for investment decisions, i.e., the energy-saving benefit of technology adoption. This information can be fed back to INVERT/EE-Lab, as indicated by the dashed arrow. However, we don't run the two models iteratively until convergence for two reasons: (1) FLEX-Operation calculates for only one year with pre-defined energy prices, while INVERT/EE-Lab simulates multiple years with changing energy prices. So, the iteration the between two models requires huge computation effort; (2) FLEX-Operation covers more technologies than

INVERT/EE-Lab (e.g., PV, battery, EV, etc.) as the two models are designed for different research questions in the first place.

3) FORECAST-Appliance is used to capture the efficiency improvement of the appliance stock, i.e., the efficiency indicator of appliance electricity consumption is used as the input for FLEX-Operation.
4) Based on the results of FLEX-Operation, FLEX-Community calculates the operation of a pre-defined energy community from the perspective of an aggregator. The aggregator maximizes its profit by (1) facilitating the P2P electricity trading within the community and (2) maximizing his profit by the charging and discharging the battery optimally.
5) FLEX-Behavior model is planned to enhance the modeling of households' behaviors (i.e., the hourly activity profiles). In the current version, the behavior profiles are generated based on the results of the HOTMAPS project (Ali Aydemir et al. 2020), e.g., electricity appliances load profiles, hot water demand, etc. (see Section 2.1.2.1).

2. MODEL

This chapter introduces the two models – Flex-Operation and FLEX-Community – that are developed in WP5 of newTRENDs. The core of the framework is an hourly system operation model of individual households (or buildings) (FLEX-Operation model, Section 2.1). Then, by extending this core part from the perspective of an aggregator, we consider the interaction among households (or buildings) in an energy community (FLEX-Community model, Section 2.2).

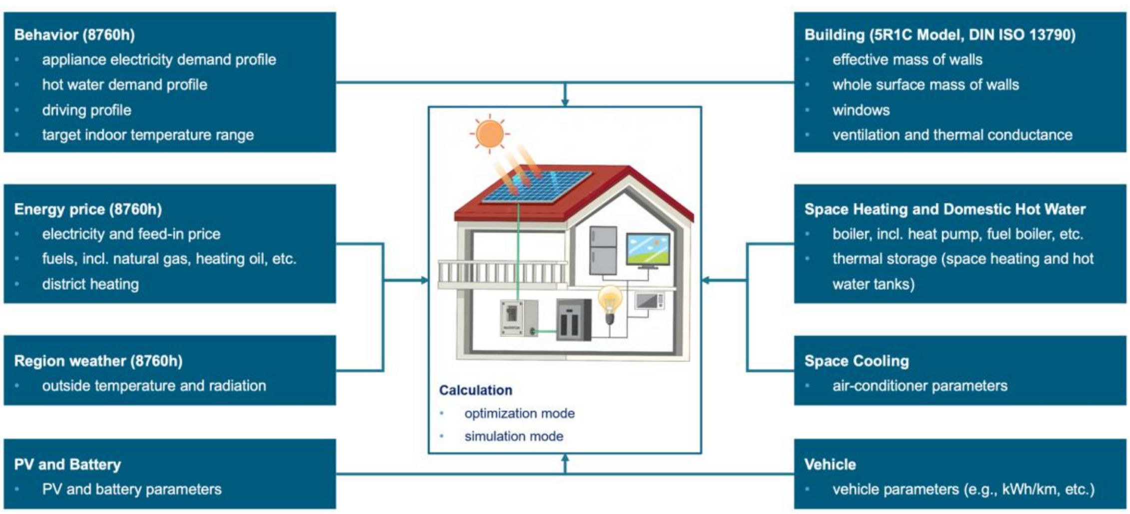
2.1 FLEX-Operation: Individual Households Modeling

2.1.1 Model Structure

To model the hourly operation of the energy system of an individual household living in a single-family house (or multiple families living in a multiple-family building), FLEX-Operation considers five energy services as follows:

1) electric appliances, e.g., television, refrigerator, lighting, etc.
2) space heating
3) domestic hot water
4) space cooling
5) vehicle

Figure 2 Model structure for individual households



Source: Own Visualization

As shown in Figure 2, the five energy services are modeled in the module "Behavior". The electric appliances are modeled together as an exogenous demand profile, and the domestic hot water demand is modeled in the same way. If the household has a vehicle, the demand is modeled by a driving profile and the respecive energy demand per kilometer travelled. Finally, the module "Behavior" also includes the household's hourly target indoor temperature range, which covers the household's bulding occupation and demand of space heating and cooling. For the case of a multiple-family building, to simplify, we calculate at the building level:

1) the profiles of appliance electricity and domestic hot water for the whole building are aggregated to the building level;
2) the target indoor temperature range and heating/cooling demand are generated and calculated for the building;
3) the vehicle demand of the multiple-family buildings is not considered.

The thermal dynamics of the building is modeled in the module "Building", which takes the following three parts as inputs to calculate the energy demand of space heating and cooling, as well as the room temperature and building mass in hourly resolution.

1) building parameters
2) target indoor temperature range
3) the weather of the region, including outside temperature and radiation

Based on the first two modules, all the "energy service demand" is converted to "useful energy demand", which is then satisfied by the technologies in the following modules: "Space Heating and Domestic Hot Water", "Space Cooling", "PV and Battery", and "Vehicle".

Finally, in the module "Calculation", depending on the technology type and parameters, the "final energy demand" is calculated for the household, as well as the total energy cost of the year. The module "Calculation" considers two modes: optimization and simulation, i.e., the model can either (1) optimize the operation of different technologies in hourly resolution through the whole year (8760 hours) to minimize the total energy cost; or (2) simulate the system based on specific operation assumptions. By comparing the results of the two modes, the impact of SEMS is shown. Prices of different energy carriers are the inputs of the module "Calculation".

2.1.2 Modules

2.1.2.1 Behavior

As introduced above, the module "Behavior" covers the following four aspects:

1) an electricity demand profile from electric appliances;
2) a domestic hot water demand profile;
3) a driving profile;
4) the target indoor temperature range.

All four aspects are exogenous inputs of the model and are in hourly resolution throughout the whole year (8760 hours).

To generate the demand profiles of appliance electricity and domestic hot water for a household (or building), we follow the three steps: (1) estimate the annual consumption amount per person: taking a typical German household as an example, it is assumed that the annual electricity consumption of appliances is 1000 kWh/person (Klingler 2018), and the annual energy consumption of domestic hot water is 500 kWh/person (BBSR 2017); (2) multiply with the total number of persons in the household (or building) to calculate the annual total consumption; (3) allocate the annual total consumption to the 8760 hours in a year following the generic demand profiles developed in the HOTMAPS project.

The driving profile of a household includes two parts: first is a binary array with ones implying the vehicle is at home and zeros indicating the vehicle is outside; second is the driving distance in each hour. The ALADIN model developed the driving profiles based on the REM 2030 driving profiles database (Gnann 2015).

Finally, the target indoor temperature range is calculated based on two inputs:

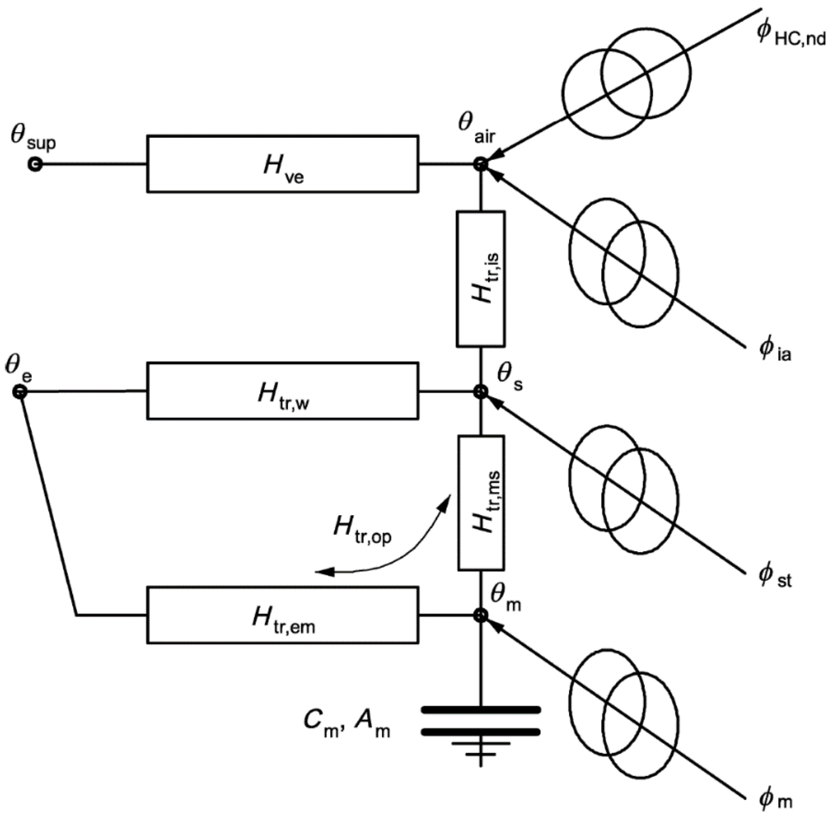
1) a binary array with ones implying that there are persons at home (heating or cooling are needed), and zeros implying that there are no persons at home. By adapting this array for a household, we can simulate different work-from-home scenarios.
2) the minimum and maximum target temperature when there are persons at home or not.

For the base scenario, it is assumed that there are always persons at home and the minimum and maximum target temperatures are 20℃ and 27℃. However, during winter, the indoor temperature is not allowed to rise above 23°C to keep indoor temperature comfort.

2.1.2.2 Building

To endogenously model the hourly thermal dynamics of a building, the model uses the 5R1C framework following DIN ISO 13790.

Figure 3 5R1C circuit representation of a building



Source: Own Visualization

As shown in Figure 3, with the 5R1C approach, a building is represented by a circuit with five resistances and one capacity. The parameters are summarized in Table 2.

Table 2 Building parameters in the 5R1C framework

Parameter	Explanation	Unit	Value or calculation
A_f	effectively used floor area	m^2	building dependent
λ	the ratio between the surface and effective area	1	$\lambda = 4.5$

Parameter	Explanation	Unit	Value or calculation
A_{tot}	the total surface area of the building	m^2	$A_{tot} = \lambda A_f$
A_j	the surface area of the building element j	m^2	building dependent
k_j	the specific thermal capacity of the building element j	$J/K \cdot m^2$	building dependent
C_m	the total thermal capacity of the building mass	J/K	$C_m = \sum(k_j \times A_j)$
A_m	effective mass-related area	m^2	$A_m = C_m^2 / \sum(k_j^2 \times A_j)$
H_{ve}	ventilation transfer coefficient	W/K	building dependent
$H_{tr,is}$	surface transfer coefficient	W/K	$H_{tr,is} = 3.45A_{tot}$
$H_{tr,w}$	window transfer coefficient	W/K	building dependent
$H_{tr,ms}$	surface transfer coefficient	W/K	$H_{tr,ms} = 9.1A_m$
H_{tr1}	heat transfer coefficient	W/K	$H_{tr1} = 1/(1/H_{ve} + 1/H_{tr,is})$
H_{tr2}	heat transfer coefficient	W/K	$H_{tr2} = H_{tr1} + H_w$
H_{tr3}	heat transfer coefficient	W/K	$H_{tr3} = 1/(1/H_{tr2} + 1/H_{tr,ms})$
H_D	external environment heat transmission coefficient	W/K	building dependent
H_g	ground heat transmission coefficient	W/K	building dependent
H_U	unconditioned room heat transmission coefficient	W/K	building dependent
H_A	adjacent buildings heat transmission coefficient	W/K	building dependent
H_{op}	Transmission coefficient through opaque building elements	W/K	$H_{op} = H_D + H_g + H_U + H_A$

Parameter	Explanation	Unit	Value or calculation
$H_{tr,em}$	effective thermal mass heat transmission coefficient	W/K	$H_{tr,em} = 1/(1/H_{op} - 1/H_{tr,ms})$

Through the 5R1C approach, the relation between outside temperature ($\theta_{outside}$), indoor temperature (θ_{air}), and heating and cooling demand (ϕ_{HC}) is provided by Equation (3.1, with ϕ representing the heat flows (W) and θ representing the temperatures (℃).

$$\theta_{air}^{t} = \frac{H_{is} \times \theta_{s}^{t} + H_{ve} \times \theta_{sup}^{t} + \phi_{ia} + \phi_{HC}^{t}}{H_{is} + H_{ve}} \tag{3.1}$$

θ_{sup} represents the air temperature from the ventilation system. When there is no heat exchanger, we have $\theta_{sup} = \theta_{outside}$.

$\phi_{ia} = 0.5\phi_{int}$, with ϕ_{int} representing the internal heat gain (W/m^2) in each hour. For simplification, we assume the internal gain is a constant parameter.

The node temperature θ_{s}^{t} is calculated with Equation (3.2 as follows:

$$\theta_{s}^{t} = \frac{H_{ms} \times \theta_{m_{avg}}^{t} + \phi_{st}^{t} + H_{w} \times \theta_{outside}^{t} + H_{tr1} \times [\theta_{sup}^{t} + (\phi_{ia} + \phi_{HC}^{t})/H_{ve}]}{H_{ms} + H_{w} + H_{tr1}} \tag{3.2}$$

$\theta_{m_{avg}}^{t}$ represents the average temperature of the building mass in the previous and current hour, calculated with Equation (3.3, (3.4, (3.5, (3.6 and (3.7.

$$\theta_{m_{avg}}^{t} = \frac{\theta_{m}^{t} + \theta_{m}^{t-1}}{2} \tag{3.3}$$

$$\theta_{m}^{t} = \frac{\theta_{m}^{t-1} \times [C_{m}/3600 - 0.5 \times (H_{tr3} + H_{em})] + \phi_{m_{tot}}^{t}}{C_{m}/3600 + 0.5 \times (H_{tr3} + H_{em})} \tag{3.4}$$

$$\begin{aligned}\phi_{m_{tot}}^{t} &= \phi_{m}^{t} + H_{em} \times \theta_{outside}^{t} \\ &\quad + H_{tr3} \times [\phi_{st}^{t} + H_{w} \times \theta_{outside}^{t} + \frac{H_{tr1}}{H_{tr2}} \times (\frac{\phi_{ia} + \phi_{HC}^{t}}{H_{ve}} + \theta_{sup}^{t})]\end{aligned} \tag{3.5}$$

$$\phi_{st}^{t} = (1 - \frac{A_{m}}{A_{t}} - \frac{H_{w}}{9.1 \times A_{t}}) \times (0.5 \times \phi_{int} + \phi_{sol}^{t}) \tag{3.6}$$

$$\phi_{m}^{t} = \frac{A_{m}}{A_{t}} \times (0.5 \times \phi_{int} + \phi_{sol}^{t}) \tag{3.7}$$

We use the reduced order representation of a single building rather than a detailed one to reduce the computational demand in both the simulation and especially in the optimization mode.

2.1.2.3 Space Heating and Domestic Hot Water

The space heating and domestic hot water demands are supported by the same "heating system" that consists of two parts:

First is the heating unit, including

1) the main boiler, which can be based on a heat pump, a fuel-based boiler (e.g., natural gas, heating oil, coal, biomass, etc.), or district heating;
2) an additional electric heating element.

The fuel-based boiler is modeled with a fixed conversion factor from fuel to useful heat. On the other hand, the heat pump's efficiency depends on the supply and source temperature after equation (3.8. For an air-sourced heat pump, the outside temperature is used. For a ground-sourced heat pump, the temperature in the ground is estimated to be constant at 10°C throughout the year. Supply temperatures are 35°C for space heating purposes and 55°C for hot water. The coefficient η represents a general carnot efficiency factor which is chosen to be 0.35 for an air sourced and 0.4 for a ground-sourced heat pump. The heating element can be used independently for hot water and heating generation by using electricity with an efficiency of 1.

$$COP_t = \eta * \frac{T_{supply}^t}{T_{supply}^t - T_{source}^t} \tag{3.8}$$

Second is the thermal storage, including two separate tanks for space heating and domestic hot water.

Both tanks are modeled according to equations (3.9 and (3.10. Q_{tank} denotes the energy currently saved in the tank. m_{water} and c_{water} describe the mass of water inside the tank and the heat capacity of the water, respectively. The temperature inside the tank is not allowed to exceed 45°C in the heating buffer storage and 65°C in the domestic hot water tank. $T_{tank}^{surrounding}$ is the temperature around the tank. It is estimated to be 20°C throughout the year. We set 28°C as the minimum temperature inside each tank. Tank losses are calculated based on the water temperature inside the tank, the surrounding temperature, and the heat transfer coefficient (Λ) over the surface of the tank walls (A_{tank}) after equation (3.10.

$$Q_{tank}^t = m_{water} * c_{water} * (T_{tank}^t - T_{tank}^{surrounding}) \tag{3.9}$$

$$Q_{tank}^{loss} = \Lambda * A_{tank} * (T_{tank}^t - T_{tank}^{surrounding}) \tag{3.10}$$

When charging a tank with a heat pump, the supply temperature is raised by 10°C, i.e., 45°C for the space heating tank and 55°C for the domestic hot water tank.

2.1.2.4 Space Cooling

For space cooling, we consider an air-conditioner with two parameters:

1) capacity, which is the maximum power of the device;
2) coefficient of performance (COP) is the electricity consumption divided by the useful energy demand.

For simplification, we assume an air-conditioner with a constant COP equaling to 3. Furthermore, we consider the "shading behavior" of households. When the outside temperature is higher than a threshold value (30℃), the household will lower the sun shade so the solar gain of that hour will be reduced by 50%.

2.1.2.5 PV and Battery

The model considers the PV and battery adoption of the household.

The hourly PV generation is downloaded from the PVGIS database[3] for a specific region and year, given the size of the PV system. To generate the representative PV generation profile for a country, we first download the profiles of NUTS-3 regions in the country, then aggregate them to the national level by taking the weighted average with regional floor area as weights. The information is taken from the HOTMAPS Database.

Concerning the battery, the model considers the following parameters:

1) the capacity of the battery (kWh);
2) charging and discharging efficiency (%);
3) the maximum charge and discharge power limit (kW).

By modeling the PV and battery system, the household can (1) produce and sell electricity as a "prosumer", and (2) manage the electricity consumption for lower cost as a "prosumager".

2.1.2.6 Vehicle

To capture the potential coupling of electric vehicles and PV adoption, the model also considers households' vehicle adoption. For comprehensiveness, the model covers both electric and gasoline vehicles.

For both types of vehicles, a "consumption rate" parameter (Wh/km) is used to model their efficiency. For an electric vehicle, the following parameters are also used:

1) the capacity of the battery (kWh);
2) charging and discharging efficiency (%);

3 https://re.jrc.ec.europa.eu/pvg_tools/en/

3) the maximum charge and discharge power limit (kW);
4) availability of bi-directional charging (boolean).

When adopted with an electric vehicle, the household can charge it with the surplus during the hours when the vehicle is at home. If the electric vehicle has the functionality of bi-directional charging, it can also be used as a battery to support the household load.

2.1.2.7 Calculation

As introduced above, the modules "Behavior" and "Building" convert the "energy service demand" to "useful energy demand". Then, based on the modules in Section 2.1.2.3-2.1.2.6, the module "Calculation" calculates the operation of the technologies in hourly resolution, as well as the "final energy consumption" and energy cost.

The module "Calculation" considers two modes: optimization and simulation. By comparing the two modes' results, the impact of SEMS is shown.

First, under the optimization mode, the model optimizes the hourly operation of all technologies adopted by the household (or building) to minimize the total annual energy cost ((3.11).

$$\min \sum_{t=1}^{8760} P_t \cdot EC_t - FIT_t \cdot ES_t \tag{3.11}$$

with t implying the hour index, p_t implying the energy price, EC_t implying the energy consumption from the grid, FIT_t implying the feed-in tariff, and ES_t implying the electricity sold to the grid.

Second, under the simulation mode, the model simulates the system operation based on specific assumptions:

1) the PV generation is used to satisfy electricity consumption directly;
2) the surplus of PV generation is saved following the order of battery, electric vehicle, and domestic hot water tank;
3) if there is still PV generation left, it is sold to the grid.

2.1.3 Implementation

FLEX-Operation is implemented in Python, and the optimization mode is set up with Pyomo[4] and solved by gurobi[5].

4 http://www.pyomo.org/

5 https://www.gurobi.com/

2.2 FLEX-Community: Energy Community Modeling

2.2.1 Model Structure

As reviewed in Section 1.2.2, the existing energy community literature simplifies individual households' modeling to reduce the optimization scale. However, this hinders the construction of an energy community with a detailed configuration of the households, e.g., building efficiency, technology adoption, etc. In this regard, FLEX-Community is built on top of the results from FLEX-Operation, i.e., the two models are soft-linked.

FLEX-Community takes the perspective of an aggregator of the community who maximizes its profit by (1) facilitating the P2P electricity trading within the community in real time, and (2) optimizing the operation of a battery. These two modules support the aggregator's business model.

2.2.2 Modules

2.2.2.1 P2P Electricity Trading

In an energy community households have heterogeneous technology adoption and behaviors. In some hours households with PV sell their surplus generation to the grid at the lower feed-in tariff. Simultaneously, other households are buying electricity from the grid at a higher price.

In such hours, the aggregator can work profitably by facilitating the P2P electricity trading among the households in real time:

1) Buy electricity at a lower price ($P_a^{bid} = \theta_a^{bid} \cdot FIT_t$), with $\theta_a^{bid} \geq 1$.
2) Sell electricity at a higher price ($P_a^{ask} = \theta_a^{ask} \cdot P_t$), with $\theta_a^{ask} \leq 1$.

From FLEX-Operation, FLEX-Community receives the results of each household in the community in hourly resolution. Then, FLEX-Community calculates the P2P electricity trading potential within the community in each hour.

As a result, the *<u>first part of the profit</u>* of the aggregator is $\pi_a^{P2P} = \sum_{t=1}^{8760}(P_a^{ask} - P_a^{bid})$, which depends on the energy community's scale and the households' heterogeneity. The larger the community is, and the more heterogeneous the households are, the higher π_a^{P2P} is for the aggregator.

As the trading happens in real time, the aggregator does not need to store the electricity. The strategy of the aggregator is captured by $(\theta_a^{bid}, \theta_a^{ask})$. Once the community and aggregator's strategy are specified, π_a^{P2P} is fixed.

2.2.2.2 Battery Operation

Apart from facilitating the real time P2P trading within the community, the aggregator can also buy the surplus electricity from the community at the price P_a^{bid}, save it in the battery, and sell it later at the price P_a^{ask}.

The aggregator's battery includes two parts: (1) a self-owned battery and (2) the remaining battery capacity of the community (result of FLEX-Operation), which changes in each hour because the households are the owners and have the preemption to use.

As a result, by optimizing the battery operation, the aggregator can earn the *second part of the profit* π_a^{OPT}, which depends on the battery capacity. The larger the battery capacity, the higher π_a^{OPT} is for the aggregator.

2.2.3 Implementation

Same with FLEX-Operation, FLEX-Community is also implemented in Python, and the optimization is setup with Pyomo and solved by gurobi.

3. INDIVIDUAL HOUSEHOLDS ANALYSIS

As introduced in Section 2.1, FLEX-Operation covers the energy consumption of an individual household, including the following five aspects:

1) electric appliances
2) space heating
3) domestic hot water
4) space cooling
5) vehicle

The behavior and technology adoption of the household can be configured in detail, as well as the temperature, solar radiation, and energy prices. By comparing the results of the optimization and by simulation of the running modes, the impact of SEMS can be revealed.

In this chapter, we present the results of individual households and analyze the impact of SEMS on energy consumption and the adoption of different technologies. Section 3.1 summarizes the scenarios, each of which represents one individual household that is configured in detail. Then, Section 3.2 presents the results of the calculation. Finally, in Section 3.3, we discuss the strengths and limitations of the model and summarize the research questions that can be analyzed with FLEX-Operation.

3.1 Scenario

In FLEX-Operation, the full definition of one scenario includes 9 components, as summarized in Table 3. In total, there are 192 exemplary scenarios.

Table 3 Scenario table of FLEX-Operation

Component	Component Scenarios		
	ID = 1	ID = 2	ID = 3
Building	High-efficiency	Mid-efficiency	Low-efficiency
Boiler	Heat pump	Gas boiler	
HeatingElement	Adopted		
SpaceHeatingTank	Adopted (750 L)	Not adopted	
HotWaterTank	Adopted (450 L)	Not adopted	
SpaceCoolingTechnology	Adopted	Not adopted	
PV	Adopted (5 kWp)	Not adopted	
Battery	Adopted (7 kWh)	Not adopted	
Vehicle	Not adopted		

In addition, there are scenario tables for the components, each of which has parameters that vary with the component's ID. For example, Table 4 shows the parameter values for each battery scenario. With a capacity equal to zero, the household is not equipped with a battery.

Table 4 Component scenario table of battery

ID_Battery	capacity	capacity_unit	charge_efficiency	charge_power_max	charge_power_max_unit	discharge_efficiency	discharge_power_max	discharge_power_max_unit
1	7000	Wh	0.95	4500	W	0.95	4500	W
2	0	Wh	0.95	4500	W	0.95	4500	W

Finally, for all the 192 scenarios, we use the data of Germany as an example, including the weather (outside temperature and radiation) and energy prices. The weather data is downloaded from the PVGIS database. The electricity price is 33.79 cent/kWh. The feed-in tariff is 7 cent/kWh and the natural gas price is 9.31 cent/kWh.

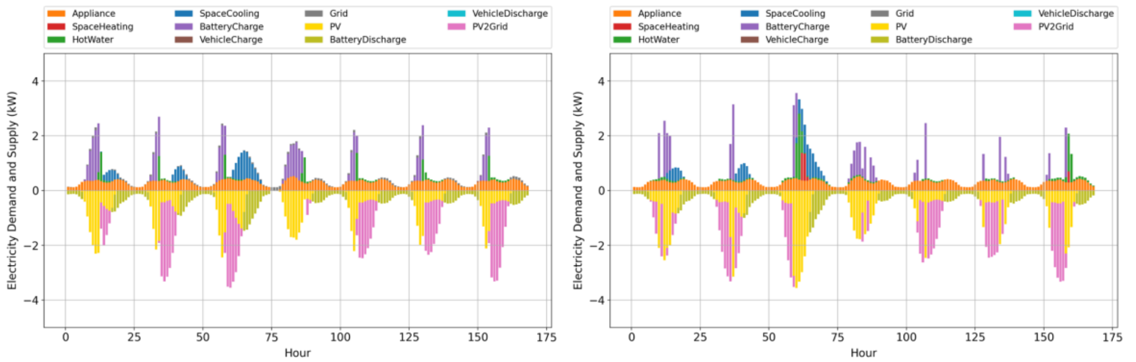
3.2 Results

3.2.1 Household Electricity Balance

Taking one representative household as an example, FLEX-Operation calculates its electricity balance in hourly resolution in both simulation and optimization modes. Figure 4 and Figure 5 show the week-long electricity demand and supply of the household in summer and winter. To the positive part of the y-axis, different parts of the bars imply the electricity demand by different technologies. In contrast, to the negative part of the y-axis, the parts of the bars indicate how the demand is satisfied.

As shown in Figure 4, the SEMS can significantly impact the load profiles by using more PV generation for domestic hot water demand. The energy is saved in the tank for later use. Similarly, for the space cooling demand on Wednesday, the SEMS also tends to pre-cool the building when there is a surplus from PV generation. The building mass saves energy. Besides, we also notice that the space heating tank is charged to maintain the minimum temperature requirement when there is PV generation. At last, if a battery is adopted, regardless of whether the SEMS is adopted, the household can rely on the PV generation for the whole week and does not need to buy electricity from the grid.

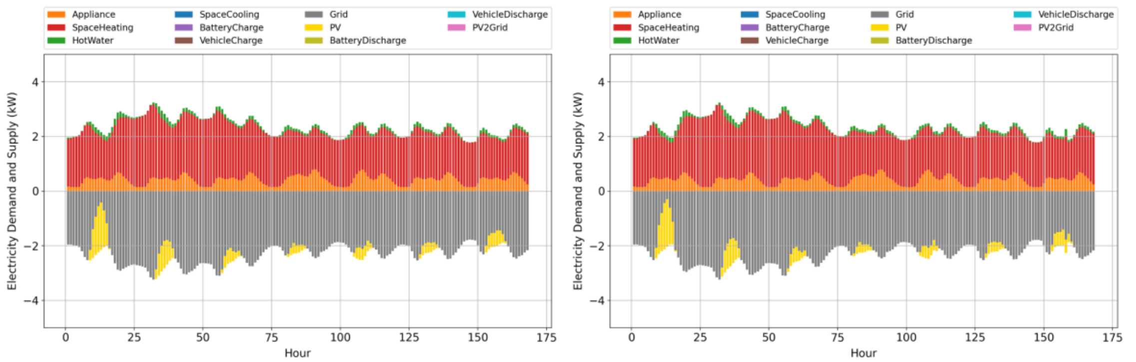
Figure 4 Electricity balance in summer (simulation-left; optimization-right)



Source: Own Calculation

Figure 5 shows the results of a winter week where the impact of SEMS is hardly visible because the PV generation is very limited in winter and used directly to support the load.

Figure 5 Electricity balance in winter (simulation-left; optimization-right)

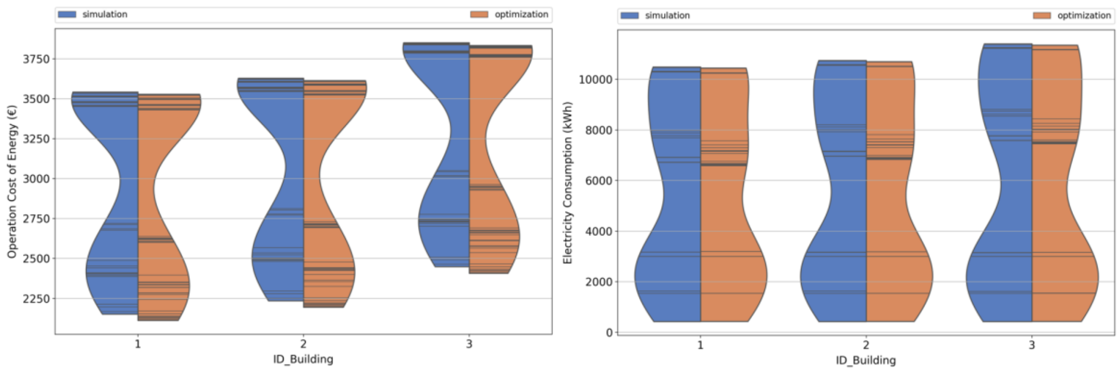


Source: Own Calculation

3.2.2 Technology Adoption Impact

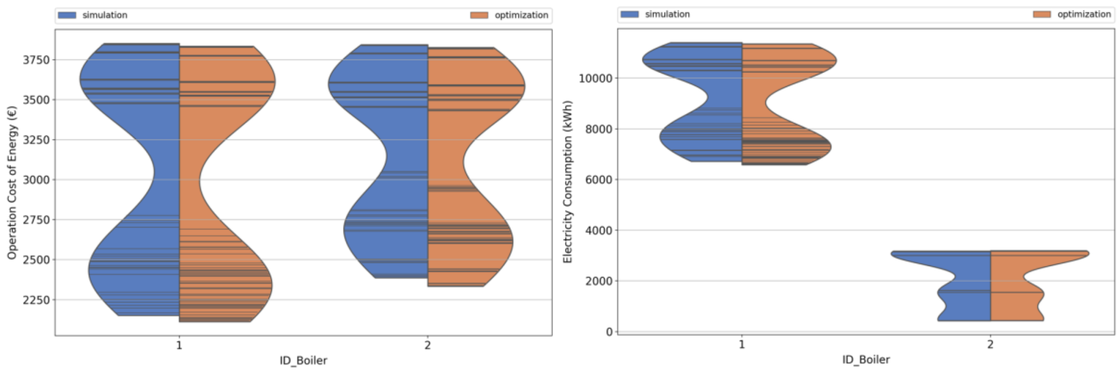
To evaluate the impact of different technologies, the 192 scenarios summarized in Section 3.1 are run in both simulation and optimization modes. Based on the results, the impact of each technology on two key annual results can be evaluated: (1) operation cost of energy and (2) electricity consumption (from the grid), as shown in Figure 6 to Figure 12.

Figure 6 Building efficiency impact on energy cost and consumption



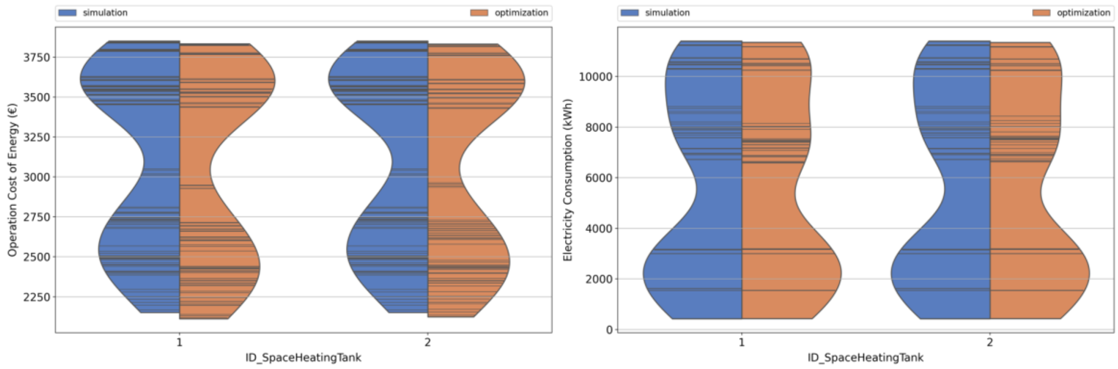
Source: Own Calculation

Figure 7 Boiler impact on energy cost and consumption



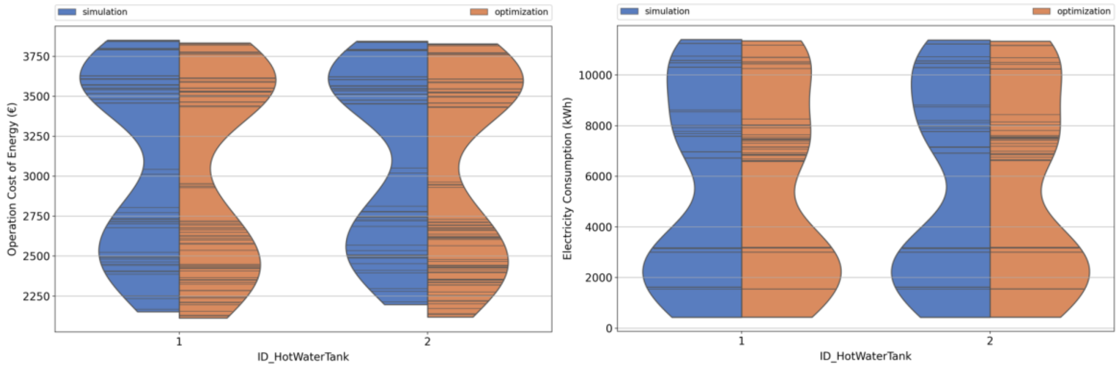
Source: Own Calculation

Figure 8 Space heating tank impact on energy cost and consumption



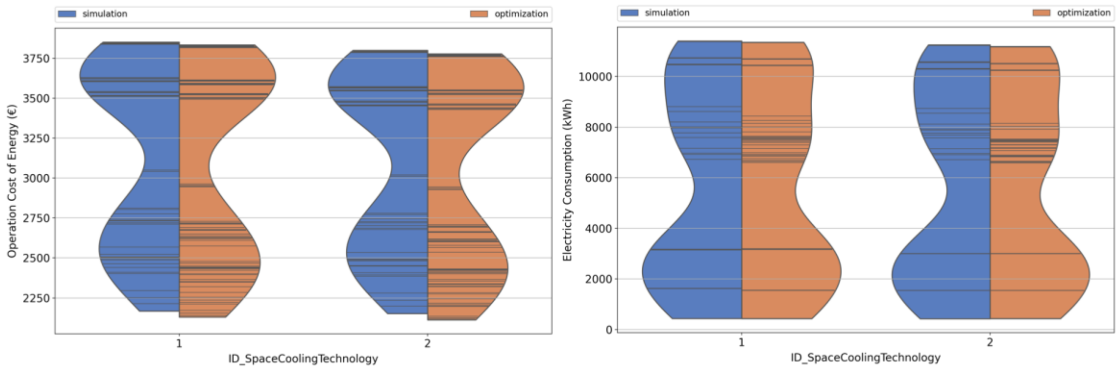
Source: Own Calculation

Figure 9 Hot water tank impact on energy cost and consumption



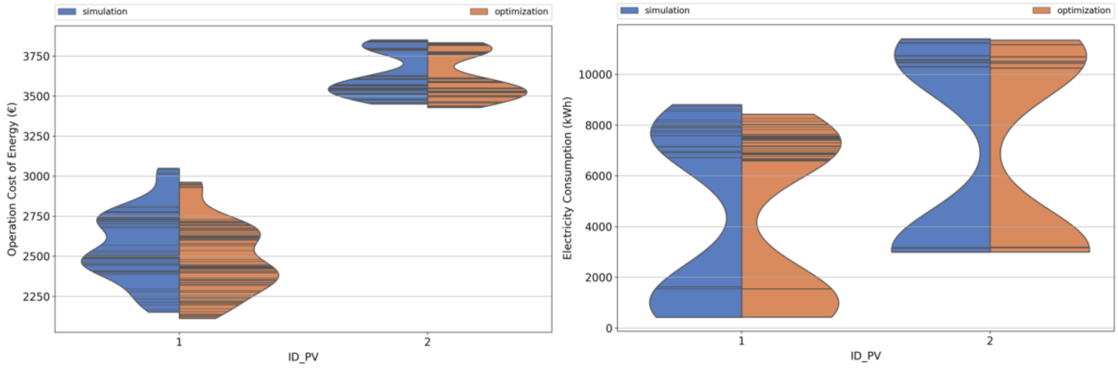
Source: Own Calculation

Figure 10 Space cooling impact on energy cost and consumption



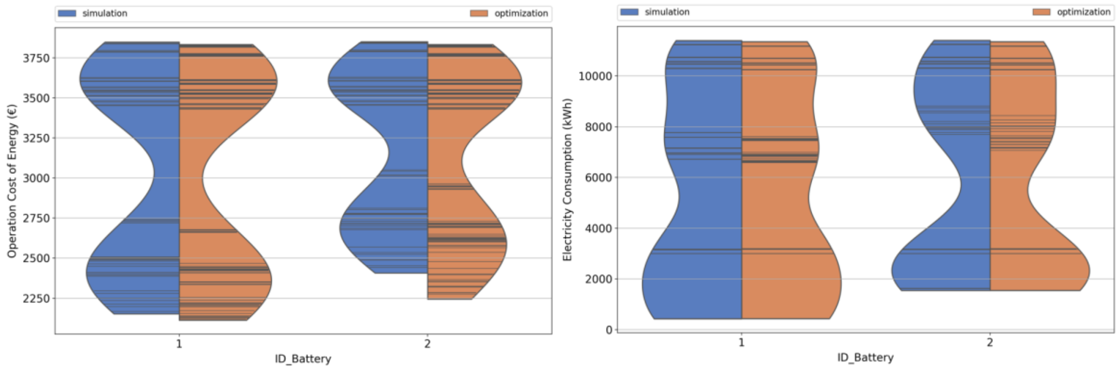
Source: Own Calculation

Figure 11 PV impact on energy cost and consumption



Source: Own Calculation

Figure 12 Battery impact on energy cost and consumption



Source: Own Calculation

From Figure 6 to Figure 12, we can summarize the following:

- The electricity consumption from the grid differs for different buildings.
- The electricity demand from the grid is strongly reduced by a PV system.
- The optimization further reduces the grid electricity demand, especially when adopting a PV system.
- The energy costs can be reduced more by the SEMS when a heat pump is installed instead of a gas boiler.
- A space heating buffer storage has a limited effect on the electricity consumption from the grid; however, it is beneficial for the optimization to reduce loads during winter.
- A battery reduces the electricity demand for buildings with a PV system. Buildings with batteries do not benefit significantly from the optimization because the battery already increases the PV self-consumption.

3.2.3 Technology Interaction

Based on the ability to configure a household's technology adoption in detail, FLEX-Operation can calculate the energy-saving benefit of the change of one component, provided that all the other components are unchanged.

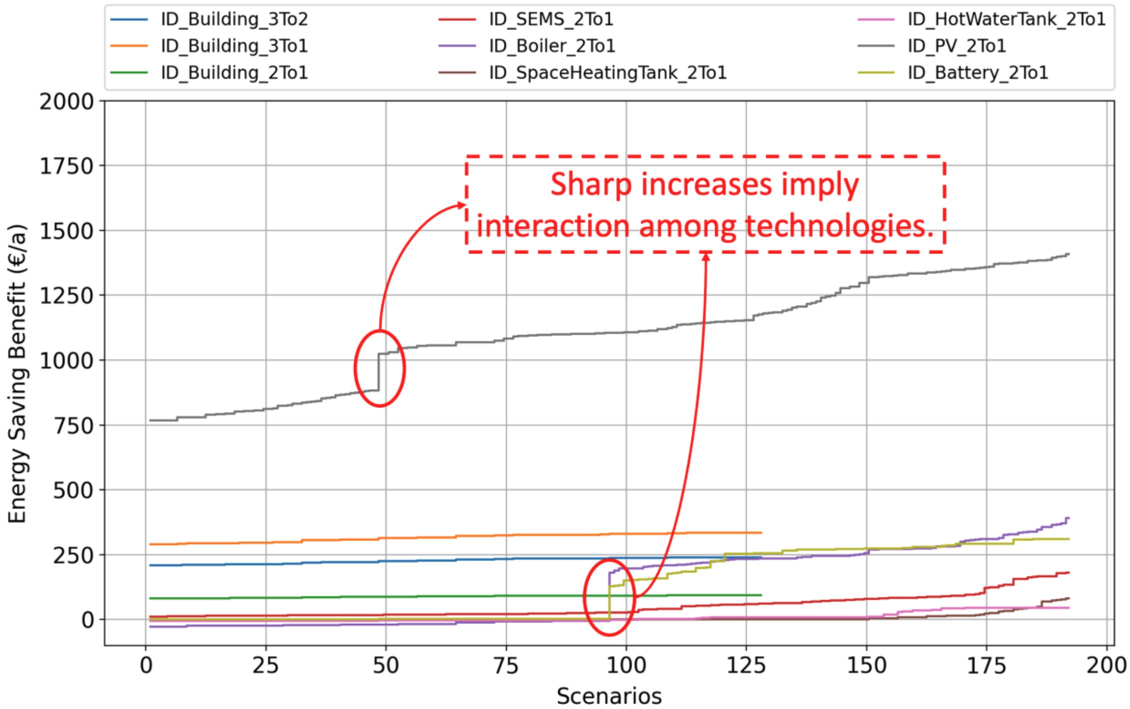
For example, Table 5 is constructed based on the FLEX-Operation results, listing 5 cases when ID_Building is changed from 3 to 2, provided that the other components are unchanged. Besides, the results of simulation and optimization modes are merged in Table 5, with ID_SEMS = 1 implying the SEMS is adopted, and the results are from the optimization mode, i.e., the SEMS is considered as a new component.

In total, given the possible combinations of other components, there are 128 cases when ID_Building can be changed from 3 to 2. After ranking the energy-saving benefit from low to high, Table 5 lists the first 5 cases.

Table 5 Energy saving benefit of ID_Building changing from 3 to 2

ID_Boiler	ID_HeatingElement	ID_SpaceHeatingTank	ID_HotWaterTank	ID_SpaceCoolingTechnology	ID_PV	ID_Battery	ID_Vehicle	ID_SEMS	ID_Building_From	ID_Building_To	EnergySaving (euro/year)
1	1	1	2	1	1	2	1	2	3	2	208.20
1	1	2	2	1	1	2	1	2	3	2	208.20
1	1	1	2	1	1	2	1	1	3	2	209.02
1	1	1	1	1	1	2	1	2	3	2	209.17
1	1	2	1	1	1	2	1	2	3	2	209.17

Figure 13 Energy saving benefit of component change

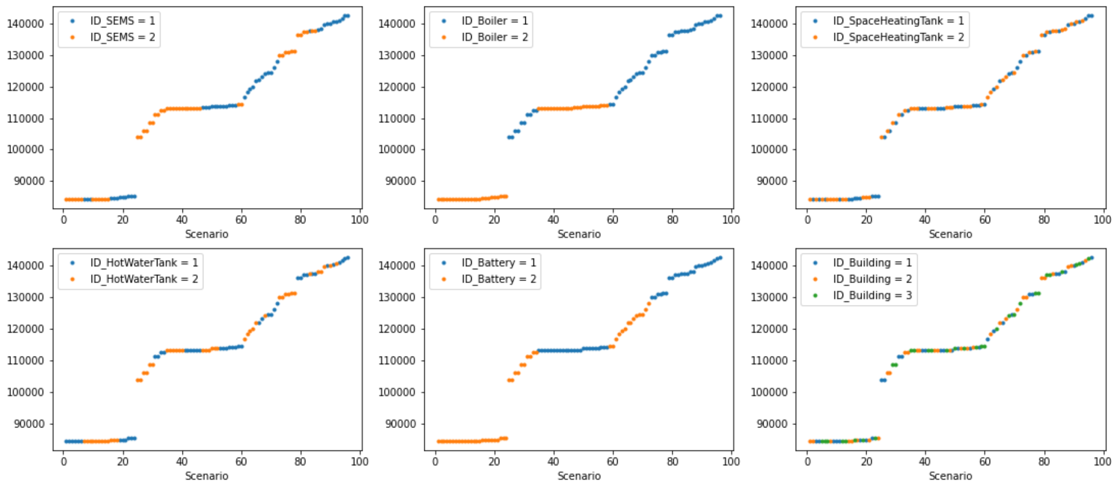


Source: Own Calculation

Then, based on the results of changing each component, we can rank the energy-saving benefit and create Figure 13, in which the marginal energy-saving benefit curve of components are plotted.

Additionally, the sharp increases in the curves indicate the interaction among technologies. For example, when a household is adopted with a heat pump, the adoption of PV can lead to significant energy savings. Figure 14 shows how different technologies can interact with the adoption of PV.

Figure 14 Interaction between different technologies and PV adoption



Source: Own Calculation

Each subplot of Figure 14 presents the interaction between one component and PV adoption. The dots in all the subplots follow the same shape, because it is the same curve of ID_PV_2To1 in Figure 13. The color of the dots implies the status of the component. The subplots show that the boiler (heat pump), battery, and SEMS significantly interact with PV adoption. Then, the domestic hot water tank (slightly) interacts with PV adoption. The space heating tank and the building efficiency hardly interact with PV adoption.

3.3 Discussions

As the name implies, FLEX-Operation focuses on the operation of a household's energy system, covering the main behaviors and technologies related to energy consumption in hourly resolution, with detailed modeling of the heat dynamics in the building based on the RC model. In Section 3.2, we showed the strengths of FLEX-Operation to calculate the load profiles of households, the impact of any component change, and the interaction between components.

The model is designed to calculate the impact of a group of factors (i.e., components of the scenario) on a household's energy consumption (amount and shape of load profile) and energy cost. The factors include:

1) Prosumaging behavior, i.e., adoption of SEMS, PV, and battery.
2) Working-from-home behavior.
3) Space heating technologies, incl. heat pump, gas boiler, etc.
4) Weather, incl. outside temperature, radiation.
5) Flat or variable electricity price.

Aggregating the results of individual households to the national level, FLEX-Operation can also provide implications on the load-shifting impact of diffusion of SEMS and PV (+ battery) system, electricity pricing mechanism, work-from-home trend, etc. Besides, FLEX-Operation can also inform the building renovation or technology adoption decision by providing its energy-saving benefit. For example, as shown in Section 3.2.3, FLEX-Operation can calculate the energy-saving benefit of building renovation and technology change (adoption/replacement) given the configuration of the other components.

However, FLEX-Operation is limited to simulating the technology change of a given building stock in yearly resolution, as done by INVERT/EE-Lab. But, combined with the investment cost of building renovation or technology adoption, FLEX-Operation can calculate the decarbonization pathway for a specific household:

1) For the options of each component, we calculate its energy-saving benefit. Then, combined with the option's investment, we can calculate the total cost of adoption/replacement.
2) Selecting the component with the lowest adoption/replacement cost and make the change.
3) Starting from the new household, proceed with steps (1) and (2).

Table 6 Decarbonization pathway of a representative building

EnergyCost (euro/year)	EnergySavingBenefit (euro/year)	ID_SEMS	ID_Building	ID_Boiler	ID_HeatingElement	ID_SpaceHeatingTank	ID_HotWaterTank	ID_SpaceCoolingTechnology	ID_PV	ID_Battery	ID_Vehicle
2130	10	1	1	1	1	1	1	1	1	1	1
2140	32	1	1	1	1	1	2	1	1	1	1
2172	42	1	1	1	1	2	2	1	1	1	1
2214	197	2	1	1	1	2	2	1	1	1	1
2410	310	2	1	2	1	2	2	1	1	1	1
2720	329	2	1	2	1	2	2	1	1	2	1
3049	789	2	3	2	1	2	2	1	1	2	1
3839		2	3	2	1	2	2	1	2	2	1

Table 6 shows an example of how a building with higher energy costs can “move up step by step”.

At the starting point, the household is configured with no SEMS (ID_SEMS = 2), a low-efficiency building (ID_Building = 3), a gas boiler (ID_Boiler = 2), no thermal or battery storage (ID_SpaceHeatingTank = 2, ID_HotWaterTank = 2, ID_Battery = 2), no PV (ID_PV = 2). The unchanged technology columns are marked in grey.

We assume the household makes decisions purely based on economic incentives but only considering the operation cost. With more information available, the investment cost can be added, together with the cost of emission embedded in the tax/subsidy of the technology and energy price.

As shown in Table 6, the household will "move up" with the following steps: (1) adopt a PV system, (2) renovate the building (efficiency level from low to high), (3) adopt a battery, (4) replace the gas boiler with a heat pump, (5) adopt the SEMS, (6) adopt a space heating tank, and (7) adopt a hot water tank. Of course, the procedure can deviate or stagnated in any state by (1) the age and lifetime of existing technologies, (2) the household's income constraint, (3) economic incentive, i.e., the household may not adopt a technology if the total cost is negative.

Finally, the results of FLEX-Operation are highly based on the behavior of the households, i.e., the activity profiles introduced in Section 2.1.2.1. Currently, we are generating the profiles based on the HOTMAPS results. With the planned FLEX-Behavior model, we can integrate more empirical evidence (e.g., the Time-of-Use survey) and more detailed behavioral assumptions (e.g., work-from-home, appliance use, driving profile) to generate the households' activity profiles. Then, these profiles are used as input for FLEX-Operation to analyze their impact on the technology operation and energy consumption.

4. ENERGY COMMUNITY ANALYSIS

As introduced in Section 2.2, FLEX-Community calculates the operation of an energy community by taking the results of individual households from FLEX-Operation, i.e., the two models are soft-linked.

In Section 4.1, we introduce the calculation scenarios, then present the FLEX-Community results from an aggregator's perspective in Section 4.2. Finally, in Section 4.3, we discuss the strengths and limitations of FLEX-Community, as well as the research questions that can be analyzed.

4.1 Scenario

The energy community scenario consists of three parts: (1) the households that participate in the community, (2) energy prices, i.e., electricity price and feed-in tariff, and (3) the strategy and endowment of the aggregator.

For a consistent setup with Chapter 3, all 192 households participate in the energy community. In addition, we assume the households are either consumers or prosumers, not prosumagers, because the aggregator of the community does the “optimization”. So, we take households’ results calculated in the simulation mode of FLEX-Operation.

Regarding the energy prices and the aggregator, the parameters are summarized in Table 7. First, we consider two scenarios for the electricity price: flat (33.79 eurocent/kWh) and variable price. The feed-in tariff is the same as in FLEX-Operation. Second, as a base scenario, we consider the aggregator a monopolist, so the bidding and asking price factors are 1.

Table 7 Scenarios of energy community analysis

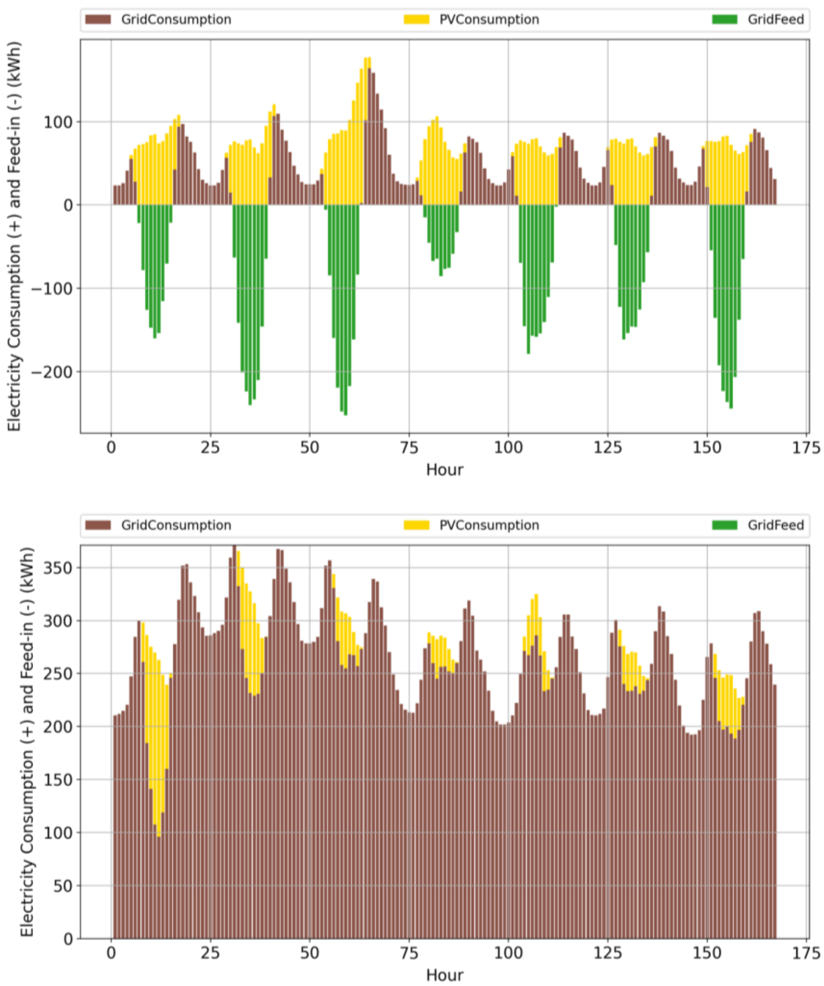
Parameter	Description	Value
$\boldsymbol{P_t}$	Electricity price.	flat or variable
$\boldsymbol{FIT_t}$	Feed-in tariff.	7 cent/kWh
$\boldsymbol{\theta_a^{bid}}$	Aggregator’s bidding price factor, $P_a^{bid} = \theta_a^{bid} \cdot FIT_t$.	1
$\boldsymbol{\theta_a^{ask}}$	Aggregator’s bidding price factor, $P_a^{ask} = \theta_a^{ask} \cdot P_t$.	1
$\boldsymbol{BAT_a}$	The size of the battery that is owned by the aggregator.	2.5 - 75MWh
$\boldsymbol{\lambda_{in}^{BAT}}$	The charging efficiency of aggregator’s battery.	0.95
$\boldsymbol{\lambda_{out}^{BAT}}$	The discharging efficiency of aggregator’s battery.	0.95
$\boldsymbol{\Omega}$	Aggregator’s control of households’ battery	Yes

As introduced in Section 2.2.2, the aggregator makes money by (1) facilitating the P2P electricity trading within the community in real time, and (2) operating a battery to maximize his profit by selling surplus electricity at a later date. The aggregator's second part of the profit depends on the size of its battery. We discuss this parameter and let it range from 2.5 MWh to 75 MWh, with a step value of 2.5 MWh. In total, there are 60 scenarios.

4.2 Results

Based on the results of the 192 housholds calculated by FLEX-Operation, Figure 15 shows the electricity balance of the energy community as a whole. Three parts are included: the consumption of PV generation, grid electricity consumption, and the feed-in electricity when there is a surplus of PV generation.

Figure 15 Community electricity balance (up–summer; bottom–winter)



Source: Own Calculation

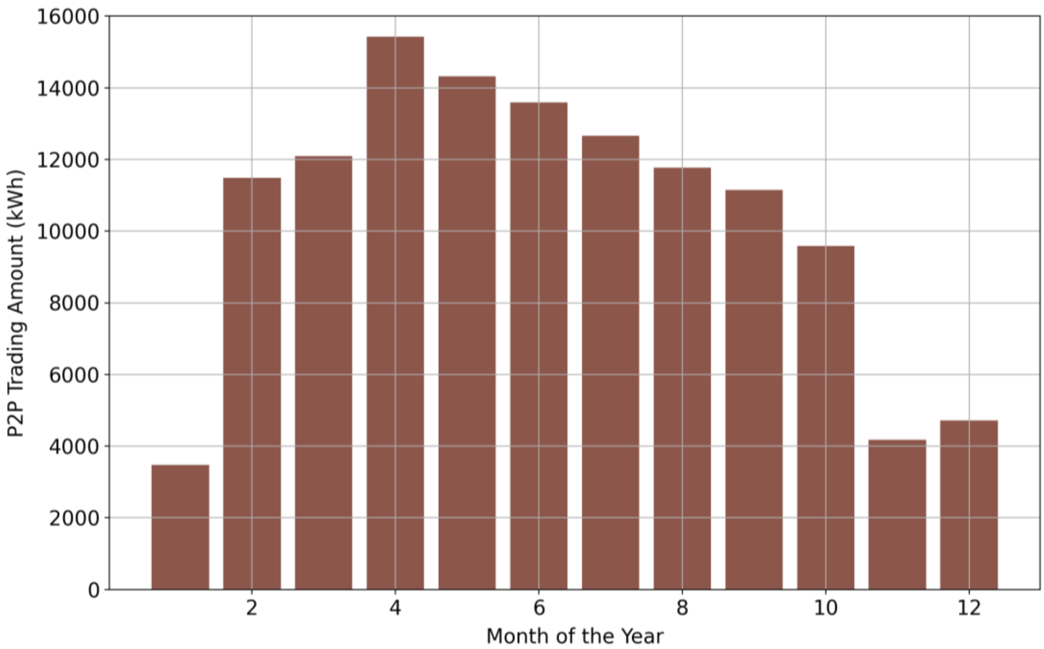
As shown in Figure 15, during the hours at noon in summer, the community has surplus PV sold to the grid. In winter, the community consumes all the PV generation. This is consistent with the balance of one household with PV (Figure 4).

4.2.1 P2P Electricity Trading

Given a community with a specified number of households (behaviors and technology adoptions), the P2P trading potential is also fixed for each hour. By enabling the P2P trading between these households, the aggregator generates the first part of its profit.

Figure 16 shows the amount of P2P trading in each month of the year. The peak is in April because heating is still needed. Those households who use heat pumps, but without PV generation, buy electricity from the other members who have surplus PV generation.

Figure 16 P2P trading amount in each month of the year



Source: Own Calculation

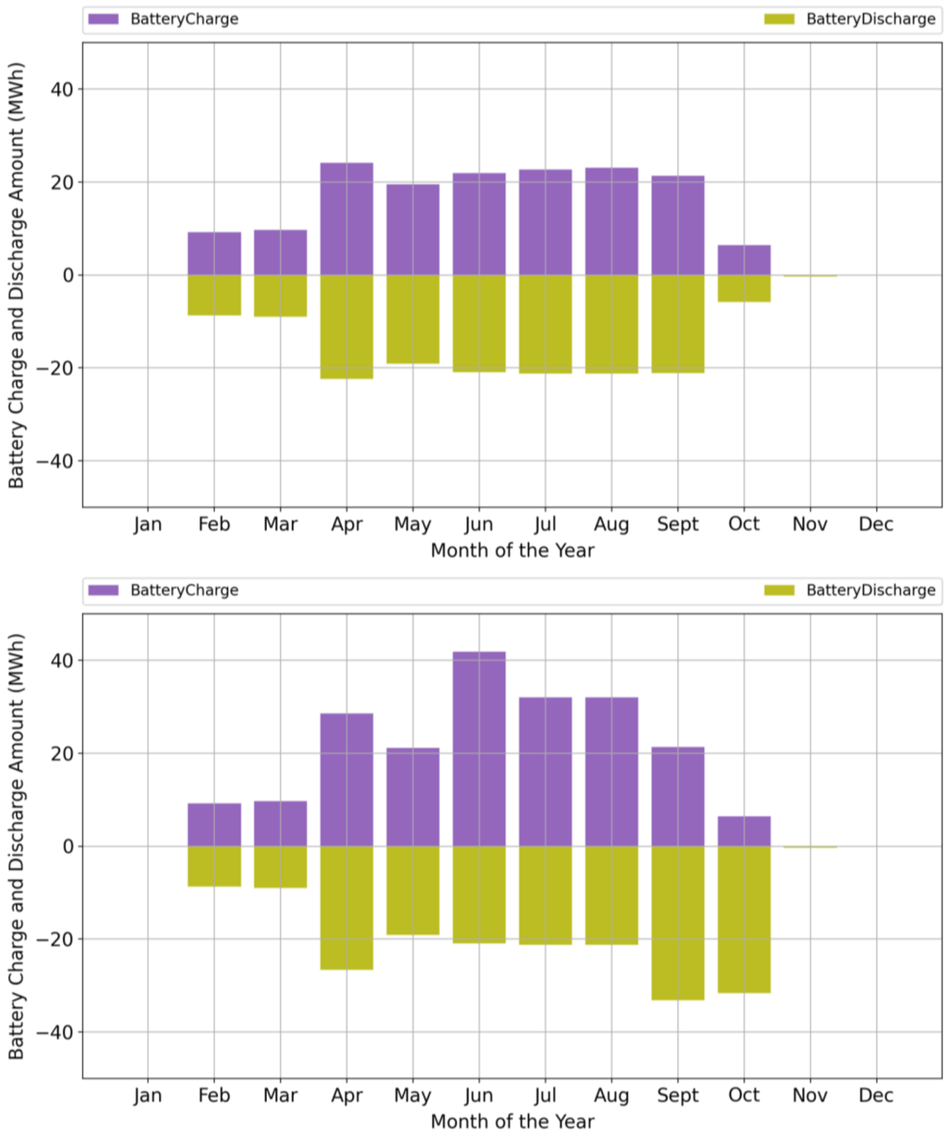
4.2.2 Battery Operation

As half of the 192 households in the community are equipped with a PV system, the net electricity surplus of the community can be saved in (1) the aggregator's battery, and (2) the remaining capacity of households' battery that are controlled by the aggregator. Then, the electricity is sold later to the grid or community members. This brings the aggregator the second part of the profit, which is determined by two factors:

- The first factor is the battery size that the aggregator can control. The larger the size is, the more flexibility the aggregator has and the more profitabel the aggregator can be.
- The second factor is the electricity price. Under variable price, the aggregator can choose to sell at a higher price and bring a higher profit.

Figure 17 and Figure 18 show the impact of these two factors on the battery operation of the aggregator.

Figure 17 Battery operation of aggregator (up-2.5 MWh, bottom-75 MWh)

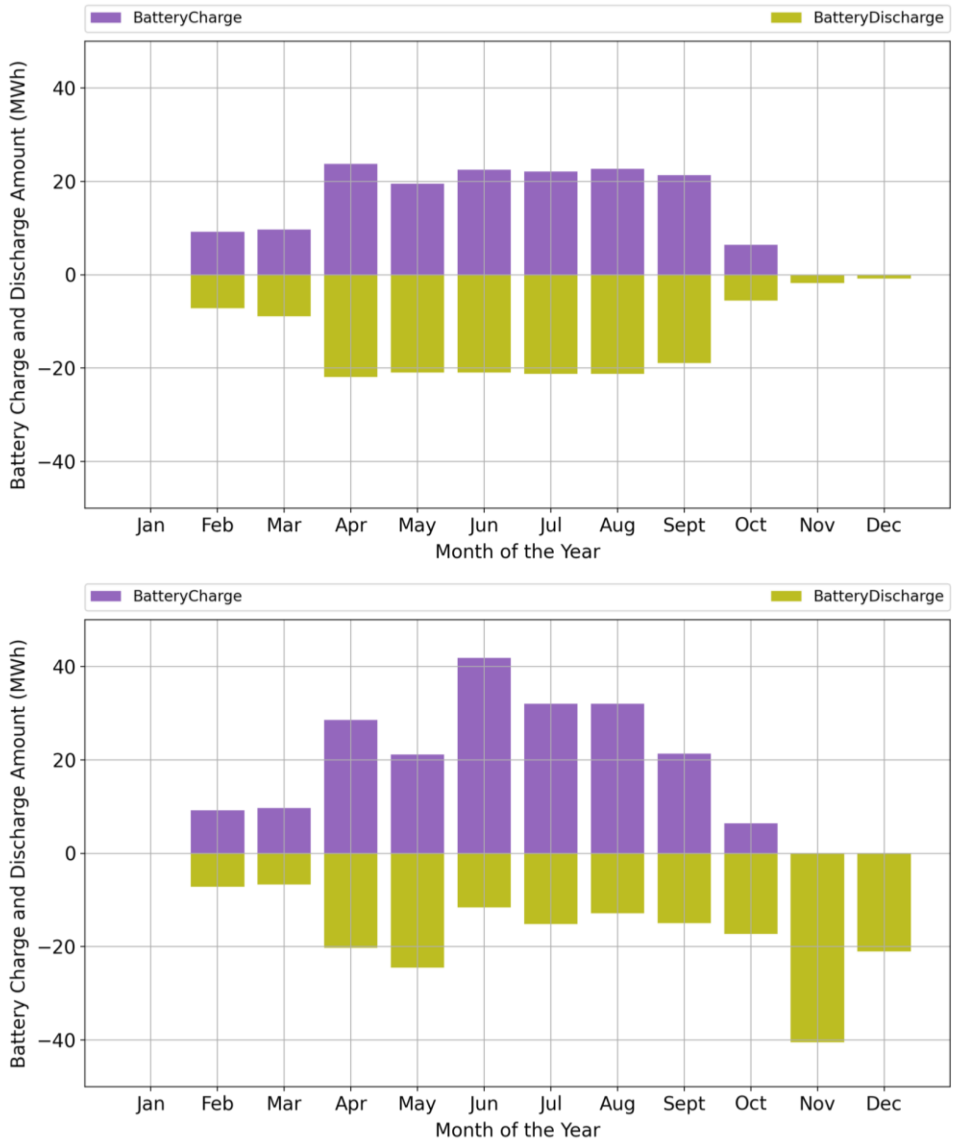


Source: Own Calculation

As shown in Figure 17, the two battery sizes are 2.5 MWh and 75 MWh and both batteries are operated under the flat (i.e. non-variable) electricity price. With a larger size of battery, the aggregator can save more electricity in June, July, and August and sell it later in September and October.

As shown in Figure 18, the two battery sizes are still 2.5 MWh and 75 MWh, but they are both operated under the variable electricity price. With a much larger battery, the aggregator can save more electricity and sell it in November and December when the electricity price has higher peak prices.

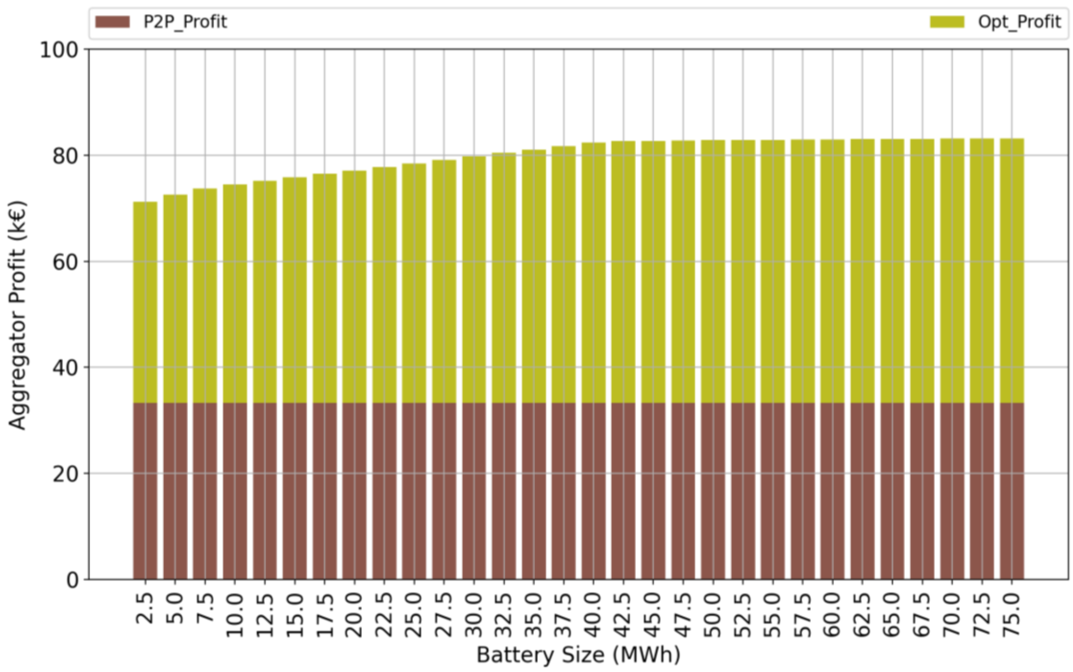
Figure 18 Battery operation of aggregator (up-flat, bottom-variable)



Source: Own Calculation

Finally, as clearly shown in Figure 17 and Figure 18, due to the limited amount of PV generation surplus in the community, the increasing battery size does not result in the same increase of electricity trading and profit. So, for a given energy community, the aggregator should choose a suitable size for the battery to maximize his profits.

Figure 19 Aggregator's total profit in relation to the battery size



Source: Own Calculation

Figure 19 shows the relation between the aggregator's total profit and the battery size. This battery size does not include the households' battery controlled by the aggregator. As shown, starting from 2.5 MWh, the total profit of the aggregator increases with the battery size, until the size of 42.5 MWh.

4.3 Discussions

By taking the results from FLEX-Operation, the main strength of FLEX-Community compared with existing models is the ability to calculate the operation of an energy community with household members defined and modeled in detail. If necessary, we can also specify an energy community involving specific types of households (incl. behaviors, buildings, and technology adoptions), and calculate the operation of the community, as well as the implications to the aggregator's profit.

The focus of this report is the modeling of prosumaging households and the energy community. So, we take the perspective of a monopolist aggregator to simplify the analysis. In fact, based on FLEX-Community, we can extend the analysis in two directions.

First, we can analyze the stability of an energy community.

For example, we can analyze the incentives of a specific household to stay in or leave the community. It can join other communities with better offers of bidding and asking prices, or it can install the SEMS and become a prosumager. Besides, the competition between aggregators can be complicated when multiple energy communities exist.

Second, it is possible that an energy community can exist without an aggregator.

On the one hand, the reasons may be that the total profit from facilitating P2P trading and battery operation is not high enough to support the business, or the households are not eager to share their system operation data with others. In such cases, there should be a general agreement among the community members on how to share the total profit.

Finally, FLEX-Community can be applied to support the aggregators designing and evaluating business models, as well as making investment decisions, for example, the self-owned battery, PV panels, etc.

5. CONCLUSIONS AND LIMITATIONS

To evaluate the impact of the new societal trends of prosumaging and energy communities on the energy demand of the building sector, this report focuses on the modeling of individual households and energy communities, and extends the framework of INVERT/EE-Lab and FORECAST-Appliance. The development of two models - FLEX-Operation and FLEX-Community - are introduced in detail in Chapter 2, followed by the analysis of the results in Chapter 3 and 4.

- FLEX-Operation supports the modeling of individual households energy demand in hourly resolution with detailed configurations of building efficiency and technology adoption. Taking the building and technology stock results from INVERT/EE-Lab and the electricity appliance efficiency indicator from FORECAST-Appliance, FLEX-Operation can calculate the load profile of residential buildings with scenarios of prosumaging and work-from-home integrated.
- FLEX-Community builds on the results of individual households from FLEX-Operation and calculates the operation of an energy community. Detailed configurations of the community members are inherited from FLEX-Operation, and the behaviors of an aggregator are also considered. The model can support the design and evaluation of the business models for an energy community, as well as the relevant investment decisions.

Besides, the development of FLEX-Behavior is planned to enhance the modeling of households' activities and provide input for FLEX-Operation. As a result, the FLEX-Behavior, FLEX-Operation, and FLEX-Community will become a modeling suite that can complement the models.

There are also limitations in the current framework:

- Even though results are generated at individual building level, they do not refer to one real building but for a group of buildings. This is a drawback of ensuring that the results can be aggregated up to national level.
- The components of a building, like the batteries, and the heating systems, are simplified. For batteries the degradation is currently not considered. In future it will however be included in the model.
- The efficiency of heat pumps is currently calculated using the carnot efficiency equation. In the future, this can be improved by modeling certain heat pumps with the python package hplib[6].
- The 5R1C approach is known to be imprecise for predicting space cooling demand. In the further, we will analyze how to mitigate this drawback by implementing additional behavior, e.g., opening windows, shading, etc. Additionally, using one capacity can be a limiting factor when simulating buildings with floor heating or thermal mass activation.

6 https://pypi.org/project/hplib/

- Electric vehicles have been proved to have a tremendous impact on the electricity consumption of single households if they are charged at home. At the same time, they offer big flexibility potential. However, their potential and their impact are highly dependent on the individual use case (driving behavior, charge at home, work etc…). Thus, the results for a single building with an electric vehicle and a certain driving profile can hardly be considered as representative a part of the building stock. A possible solution would be sheer computational power and calculating many buildings with different driving profiles. For the same reasons, we do not consider the vehicle demand in multiple-family buildings.

Finally, in the next stage, we aim to apply the model with the linkage of other sectoral models and calculate the overall decarbonization and newTRENDs scenarios for the EU.

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