Modeling households' behavior, energy system operation, and interaction in the energy community★

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ABSTRACT

Technological advancements and behavior shifts are reshaping households energy consumption patterns, necessitating advanced models to quantify their behavior, energy system operation, and interactions in the energy communities. While various models address these aspects individually, there is a lack of a unified framework that covers them holistically. This paper presents FLEX, a modeling suite consisting three interconnected components that are designed to feed the output of one into the next. First is FLEX-Behavior, which simulates hourly household energy demands using a time-dependent Markov core based on Time-use Survey data. Second is FLEX-Operation, which models hourly operation of household energy systems — incl. heating, photovoltaics, storages, vehicles, and energy management — across three modes: simulation, perfect-forecasting optimization, and rolling-horizon optimization. Third is FLEX-Community, which models the peer-to-peer electricity trading among community members and battery operation of the aggregator. Additionally, FLEX-Behavior and FLEX-Operation are validated using empirical data and detailed physics-based building simulation software, ensuring reliability in diverse applications. As a result, we simulated the behavior and energy demand of five representative households in Germany, and looked into the system operation for one of them in detail. Finally, we constructed an energy community including 640 households with heterogeneous technology adoptions and analyzed its operation and the aggregator's strategy. In summary, FLEX provides a consistent framework for analyzing impacts of technological and behavioral changes on household energy consumption, particularly in the context of societal shifts such as teleworking and the evolution from consumers to "prosumagers", who actively manage their energy consumption.

1. Introduction

Combining heat pumps (HP), photovoltaic (PV) systems, energy storage, and smart energy management systems (SEMS) can significantly contribute to a carbon-neutral household sector in three key ways. First, heat supply can be decarbonized through the use of electricity. Second, PV systems introduce more distributed renewable generation at the household level. Third, energy storage and SEMS enable households to provide flexibility to the power system. Energy storage can take the form of (1) battery storage, either installed at home or integrated into electric vehicles (EVs), and (2) thermal storage, including the buildings thermal mass or water tanks. This is especially effective when HPs are smartly controlled in response to dynamic electricity pricing. Beyond these technologies, household behaviors also play a crucial role in the transition. For example, (1) teleworking influences building occupancy and heating/cooling demand, (2) EV driving behavior affects its interactions with other technologies, and (3) the emergence of "energy

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communities" where end-users trade electricity among themselves or through an aggregator, adds new dimensions to energy management.

To better understand the integration of the technologies and the behavioral aspects, existing modeling approaches can be broadly categorized into three key strands. First is *household behavior modeling*, which captures households' behavior, including occupant status (e.g., absence, presence, number of occupants, etc.), energy behaviors, and behavioral efficiency [1]. Especially, many studies focus on the impact of occupants' behavior on the electric load profiles. With more micro-data available, studies have switched from top-down approaches [2, 3] to bottom-up simulation. In this context, Ref. [4] developed a model based on the time-use survey (TUS) data, with the behaviors of individual occupants modeled by a Markov chain, i.e., occupants switching from one activity to another according to the probabilities in a Markov matrix. Ref. [5] improved the approach by (1) considering activities' time-dependent "duration" probabilities, and (2) covering the profiles of hot water demand and driving. Ref. [6] presented a comprehensive review of the available TUS datasets, modeling methods, and implementations in building energy research. Besides, for the remote areas where no TUS data is available, there are also stochastic models developed based on interview data [7, 8].

Second is *household energy system modeling*, which focuses on the operation of a household's energy system and the final energy consumption. A major part of this type of model is to calculate the heating and cooling demand of the building, by two physics-based modeling approaches:

- First is sophisticated modeling software that can calculate the space heating and cooling demand of an individual building in detail, e.g., TRNSYS[1], EnergyPlus[2], IDA ICE[3], etc. These models are more precise, but the main drawback is the high computational effort and the high requirement for building information.

- Second are simplified models where a building is modeled as resistances and capacities (i.e., "RC models"). These models are not as detailed as the first category but are still suitable to calculate energy demand at the hourly resolution while needing less computational resources [9], which makes it possible to integrate them into an optimization algorithm. By comparing the 5R1C approach (DIN ISO 13790[4]) with TRNSYS and EnergyPlus, Refs [10, 11] showed that the 5R1C approach can balance the details of building modeling and the computation demand of optimization.

Several studies combined the building modeling with other energy consumption and technologies (incl. hot water, electric appliances, PV, battery, and EV) in an optimization framework. The objectives include the minimization of energy cost [12, 13, 14], maximization of the self-consumption rate of a PV system [15], and peak reduction [16]. Based on these models, the following questions can be analyzed (1) the operation strategy of the energy storage; (2) the optimal size of a PV plus battery system; (3) the potential of load shifting; and (4) the impact of variable electricity prices. Ref. [17] summarized the recent modeling studies and their coverage of the major components. Furthermore, the optimization includes two types: perfect-forecasting optimization over the whole year [13] and rolling-horizon optimization with a moving time window [18].

Third is *energy community modeling*. Along with households changing from consumers to prosumers/prosumagers, energy communities are also expected to play a significant role in the energy transition, since individual households are too small to join the electricity markets. Reasons for participating in a community are decreasing energy costs and addressing climate change, as well as the community spirit [19]. 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 and in the balancing market to minimize the imbalance costs [20]. 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 [21]. Ref. [22] reviewed the business models an aggregator can implement by trading the flexibility obtained from community participants in different electricity markets.

Most existing literature model energy communities at the micro-grid level [23] without details of the community members. Ref. [24] focuses on the P2P trading of PV generation in the community, and different models are used to

[1] https://www.trnsys.com

[2] https://energyplus.net

[3] https://www.equa.se/en/ida-ice

[4] DIN ISO 13790 has been replaced by ISO 52016, which is more detailed and models each building element separately. However, from the modeling perspective, it also demands more detailed building data and leads to higher computational effort, especially in operation optimization.

determine the economic benefits for each member. Ref. [25] compared different options to integrate energy systems into an energy community (e.g., community microgrids, virtual power plants, energy hubs, prosumer community groups, etc.). Ref. [26] 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. Given all the possible options, PV systems are the most established [24] and of particular interest to energy communities. Ref. [27] 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 further increased and the peak demands can be shaved even more [28]. Finally, by sharing the investment costs, individual households' risk of investing in batteries can be reduced. However, the study also suggests that thermal storage may be more attractive financially because of the high battery costs. From the perspective of aggregators, Ref. [29] analyzed their participation in the day-ahead and balancing markets 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 Ref. [30], the increased peak demand of an electrified heating network can be substantially reduced by employing an energy community.

In summary, while various models addressing household behavior, energy system operation, and energy communities have been developed within the literature, two key gaps remain, which motivate our work. First, a consistent framework that fully integrates all three parts is lacking. By "consistent framework" we refer to a structure in which interconnected components are designed to feed the output of one model into the next. This ensures that detailed assumptions made at the outset are consistently carried through to the final model. Second, in the context of energy communities, individual households are often modeled in a simplified manner, overlooking both their technological and behavioral details, as well as the consequent impacts. For example, Ref. [31] models the aggregator minimizing the imbalances, in which the loads are classified as non-flexible, semi-flexible, and flexible. No individual households are specifically modeled, neither their technology configurations (e.g., share of households with PV or EV installations) nor their behaviors (e.g., teleworking, high/low set temperature for heating and cooling).

So, in this paper, we develop the FLEX modeling suite to capture the details from both technology and behavioral aspects, covering households' behavior, energy system operation, and their interaction in an energy community. There are three models in the FLEX modeling suite:

- First is *FLEX-Behavior*, which models the energy-related behavior of a specified household. For each individual household member, the activity profile is modeled at a 10-minute resolution based on a Markov chain model. Then, the activity profile is converted to the profiles of appliance electricity and hot water demand, as well as building occupancy based on assigned locations of the activities. Finally, household members' profiles are aggregated to the household level in hourly resolution.

- Second is *FLEX-Operation*, which focuses on the operation of the household's energy system. Taking the results from *FLEX-Behavior*, *FLEX-Operation* is further configured with the household's building envelope and technology system, including the heating system, PV, thermal and battery storage, and EV. The model calculates the system operation in hourly resolution, as well as the energy consumption and cost. It can run in three modes: simulation, perfect-forecasting optimization, and rolling-horizon optimization.

- Third is *FLEX-Community*, which takes a group of households' results from *FLEX-Operation* as input and models the operation of an energy community from an aggregator's perspective. The aggregator can make a profit by using two options: (1) Facilitate the peer-to-peer (P2P) electricity trading among the households in real-time, and (2) Optimize the operation of the batteries of its own or community members to buy at lower prices and sell at higher.

Through the three models, FLEX captures the households' behavior, energy system operation, and interactions in an energy community at an hourly resolution. The correlation between households' behaviors, HP and storage operation, PV generation, and load shifting supported by the SEMS can be captured and analyzed. By comparing the costs of different technology configurations, FLEX can show the counterfactual impact of technology adoptions on energy consumption and cost, as well as the impact at the community level. The rest of this paper is organized as follows. Section 2 introduces the three models in FLEX in detail, followed by the demonstrating results in Section 3. In Section 4, we discuss the potential applications and limitations of the FLEX suite. Finally, we conclude in Section 5.

Table 1
Reclassified activity categories

ID	Activity Category	Location	Related Appliances (trigger probability)
1	Sleeping	Home	No appliance (1.00).
2	Eating and drinking	Home/Outside	No appliance (1.00).
3	Hygiene and dressing	Home	No appliance (0.20), Hot water (0.27), toothbrush (0.09), shaver (0.09), hair dryer (0.27), and hair iron (0.09).
4	Meal preparation	Home	No appliance (0.10), stove(0.27), oven (0.15), microwave (0.22), pressure cooker (0.03), sandwich maker(0.03), toaster (0.05), blender mixer (0.03), water kettle (0.05), and coffee machine (0.06).
5	Dish washing	Home	No appliance (0.20), dishwasher (0.32) and hot water (0.48).
6	Cleaning home	Home	No appliance (0.20), hot water (0.24) and vacuum cleaner (0.56).
7	Doing laundry	Home	Washing machine (1.00).
8	Ironing and maintaining clothes	Home	Electric iron (0.80) and sewing machine (0.20).
9	Entertainment	Home/Outside	Computer (0.21), laptop (0.12), tablet (0.09), mobile phone (0.16), television (0.16), projector (0.06), game console (0.15), and speaker amplifier (0.01).
10	Other activities at home	Home	No appliance (1.00).
11	Working	Home/Outside	No appliance (0.10), computer (0.41), laptop (0.24), tablet (0.06), mobile phone (0.11), and printer (0.08).
12	Education	Home/Outside	No appliance (0.10), computer (0.24), laptop (0.41), tablet (0.06), mobile phone (0.11), and printer (0.08).
13	Other activities outside of home	Outside	No appliance (1.00).
14	Other journey	Outside	No appliance (1.00).
15	Commuting to work or study	Outside	No appliance (1.00).
16	Maintenance work at home	Home	Lawnmower (0.46) and electric tools (0.54).
17	Taking break at work or school	Outside	Mobile phone (0.42), microwave (0.11), sandwich maker (0.08), toaster (0.08), water kettle (0.14), and coffee machine (0.17).

2. Model

2.1. FLEX-Behavior

FLEX-Behavior models the energy demand and building occupancy profiles of a specified household in hourly resolution. For this, the model starts by modeling the activity profiles of individual household members, based on the time-use survey[5] data from Germany.

The diaries from the survey respondents consist of 165 coded distinct activities in 10-minute intervals. In addition, participants also filled out a questionnaire regarding the social-demographic information. To reduce model complexity, the 165 TUS activities are reclassified into 17 categories as listed in Table 1. We try to minimize the number of categories for better estimation quality and also try to group the activities using a similar set of appliances. So, on one hand, there is the very specific category 8 “ironing and maintaining clothes” which can trigger the use of an electric iron and sewing machine; and there is also the general category 11 “working” which relates to a bunch of appliances including computer, laptop, etc. Finally, some activity categories are classified because they imply the specific location of the person, e.g., “other activities at home”, “commuting to work or study”, etc.

Furthermore, based on the social-demographic data in TUS, we defined four person types, including

[5]Every decade, the Federal Statistical Office in Germany conducts a large-scale, representative survey to record the time-use of its citizens. Due to the availability of micro-level data, this study uses the survey conducted from August 2012 to July 2013, covering over 12000 individuals from 5040 households, across various social demographics and household sizes. They were asked to keep detailed records of their daily activities for three pre-determined days (two weekdays, and one weekend day).

1. fully-employed adults (age between 20 to 65);
2. partly-employed adults (age between 20 to 65);
3. students (younger than 20);
4. retired persons (older than 65).

For each person type, the data is filtered and used to estimate a time-dependent Markov model which simulates the person's switching between different activities in 10-minute resolution in two types of days, weekday (from Monday to Friday) and weekend (Saturday and Sunday), through a whole year (52560 time steps). The generation follows the three steps below:

- First, at the beginning of a day (0:00 midnight), a starting activity is selected according to the TUS data. For example, for a fully-employed adult, at 0:00 on a weekday, the probability of "sleeping" is 86.52%. Then, the duration of "sleeping" is drawn according to an estimated distribution depending on (1) person type, (2) day type, and (3) time. We estimate the duration distribution of one activity depending on time to reflect the fact that, for example, "sleeping" lasts longer if it starts from 0:00 than noon.

- Second, by the end of the "sleeping" activity, the next activity is selected according to a Markov matrix as described by Equation 1. $\boldsymbol{P}$ denotes the matrix where each element at index (i, j) represents the probability switching from activity i to j, which is also estimated to be time-dependent ($t \geq 2$).

$$\boldsymbol{P} = \begin{bmatrix} p_{11}(t) & p_{12}(t) & \cdots & p_{1n}(t) \\ p_{21}(t) & p_{22}(t) & \cdots & p_{2n}(t) \\ \vdots & \vdots & \ddots & \vdots \\ p_{n1}(t) & p_{n2}(t) & \cdots & p_{nn}(t) \end{bmatrix} \quad \text{where} \sum_{j=1}^{n} p_{i,j} = 1, \text{ for any } 1 \leq i \leq n \tag{1}$$

- Third, after switching to the new activity, the model will draw its duration from a distribution, again depending on (1) person type, (2) day type, and (3) time.

By repeating Steps 2 and 3 recursively, the model generates the activity profile until the end of the day. Then, the model starts again from Step 1 for the next day. The whole process continues until the activity profile of the whole year is generated for the person. Figure 1 shows an example of the activity pattern of a fully-employed adult on weekdays, comparing the TUS data (left) and model results (right).

Taking the generated activity profile as an intermediate result, FLEX-Behavior converts it to the demand profiles of appliance electricity and hot water, as well as the location profile of the person. Each activity is related to a location and a group of appliances triggered by pre-defined probabilities (see Table 1). The probabilities are developed based on the ownership rate then calibrated so that (1) the electricity demand profiles are reasonably close to the profiles from empirical studies [32] with peaks in the evening and around noon, and (2) the annual electricity demand is close to the Destatis data [33] (see Section 3). Finally, we combine the assumption of "teleworking" with the generated profiles. If a person is doing "teleworking" on a specific day, the activities "working" and "taking break at work or school" will be counted as "at home", as well as energy consumption during that time. Finally, FLEX-Behavior aggregates the members' profiles to the household level in hourly resolution.

2.2. FLEX-Operation

FLEX-Operation models the hourly operation of a household's energy system covering the final energy demand for five services: (1) electric appliances (e.g., lighting, television, refrigerator, etc.), (2) domestic hot water, (3) space heating, (4) space cooling, and (5) vehicle. As shown in Figure 2, the "Behavior" module takes the results of FLEX-Behavior as input, including the demand profiles of appliance electricity and domestic hot water, as well as the hourly target indoor temperature range developed based on the occupancy profile, with minimum and maximum set temperature assumed for the building being occupied or not. Optionally, FLEX-Operation can also include vehicles by taking the driving profile as input. The vehicle can be either electric or with a combustion engine. When it is an electric vehicle, its charging profile can be optimized with other technologies with SEMS installation.

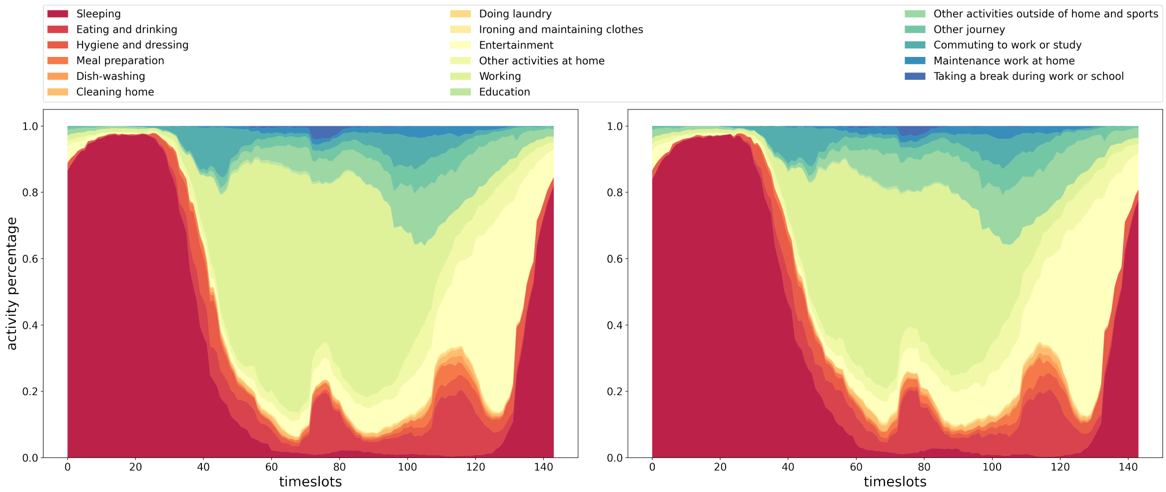


Figure 1: Activity pattern of a fully-employed adult on weekdays: German TUS data (left) and model results (right)

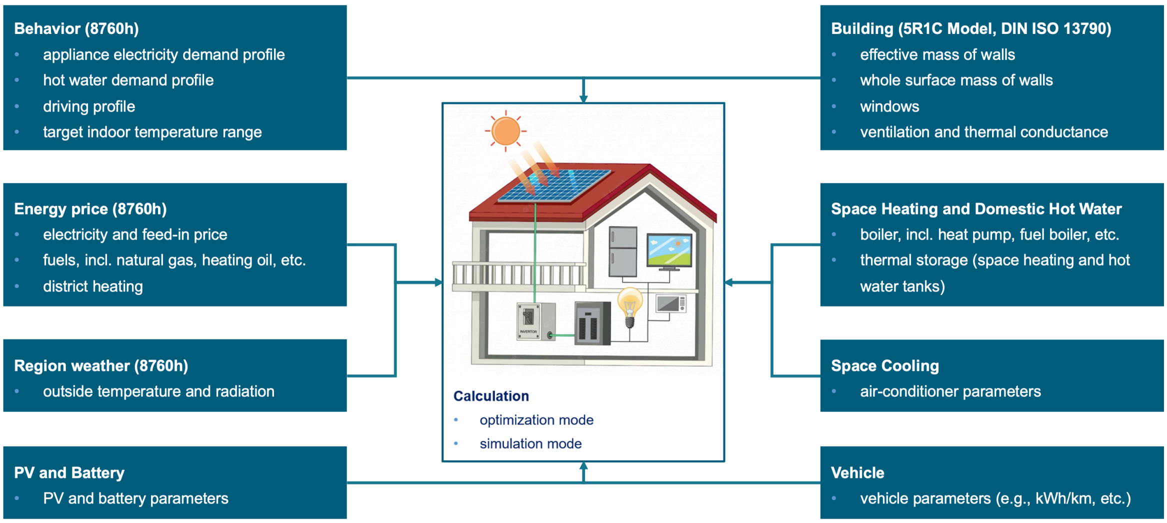
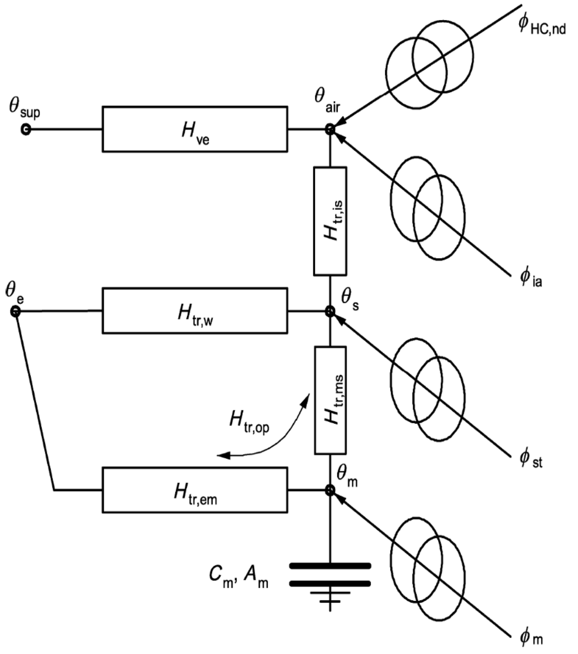


Figure 2: Structure of the FLEX-Operation model

2.2.1. *Heating and Cooling Demand Modeling*

Given the target indoor temperature range and the environment temperature, the building's heating and cooling demand are modeled with the 5R1C approach following DIN ISO 13790. The circuit model is presented in Figure 3, together with a group of selected equations. The related parameters are summarized in Table 2. A detailed description of the methodology can be found in DIN ISO 13790.

As shown in Figure 3, the relation between indoor temperature (θ_{air}), environment temperature (θ_e), and heating&cooling demand ($\phi_{HC,nd}$) is presented by Equation (a), with ϕ representing the heat flows (unit: W) and θ representing the temperatures (unit: $°C$). θ_{sup} means the air temperature from the ventilation system. In our study, we assume there is no heat exchanger installed in the ventilation system, so we have $\theta_{sup} = \theta_e$. ϕ_{int} means internal gains and we have $\phi_{ia} = 0.5\phi_{int}$. The node temperature θ_s^t is calculated with Equation (b), in which θ_{ma}^t represents the average temperature of the building mass in the previous (θ_m^{t-1}) and current (θ_m^t) hour, as calculated by the Equation (c). Specifically, θ_m^t is calculated by Equation (d), with $\phi_{m\_tot}^t$ denoting the net heat gain (i.e., internal and solar gains minus loss), calculated in Equations (e)-(g). ϕ_{sol}^t means the solar gain.



5R1C representation of the building

$$\theta^t_{air} = \frac{H_{tr,is}\theta^t_s + H_{ve}\theta^t_e + \phi^t_{ia} + \phi^t_{HC,nd}}{H_{tr,is} + H_{ve}} \quad \text{(a)}$$

$$\theta^t_s = \frac{H_{tr,ms}\theta^t_{ma} + \phi^t_{st} + H_{tr,w}\theta^t_e + H_{tr1}[\theta^t_e + \frac{\phi^t_{ia}+\phi^t_{HC,nd}}{H_{ve}}]}{H_{tr,ms} + H_{tr,w} + H_{tr1}} \quad \text{(b)}$$

$$\theta^t_{ma} = \frac{(\theta^t_m + \theta^{t-1}_m)}{2} \quad \text{(c)}$$

$$\theta^t_m = \frac{\theta^{t-1}_m[C_m/3600 - 0.5(H_{tr3} + H_{tr,em})] + \phi^t_{m\_tot}}{C_m/3600 + 0.5(H_{tr3} + H_{tr,em})} \quad \text{(d)}$$

$$\phi^t_{m\_tot} = \phi^t_m + H_{tr3}\phi^t_{st} + H_{tr,em}\theta^t_e + H_{tr3}H_{tr,w}\theta^t_e + \frac{H_{tr3}H_{tr1}}{H_{tr2}}(\frac{\phi^t_{ia} + \phi^t_{HC,nd}}{H_{ve}} + \theta^t_e) \quad \text{(e)}$$

$$\phi^t_m = \frac{A_m}{A_t}(0.5\phi^t_{int} + \phi^t_{sol}) \quad \text{(f)}$$

$$\phi^t_{st} = (1 - \frac{A_m}{A_t} - \frac{H_{tr,w}}{9.1A_t})(0.5\phi^t_{int} + \phi^t_{sol}) \quad \text{(g)}$$

Figure 3: Circuit model for the building and key equations from DIN ISO 13790

The key advantage of using this simplified 5R1C approach is that, the building mass is considered as a thermal storage in the calculation, which can be further integrated into the operation optimization including all technologies in the building. When SEMS is installed, the heat pump can be smartly controlled to pre-heat the building when the electricity price is lower. The heat can be stored in the building mass.

For validation, we compared the results of FLEX-Operation with detailed physics-based building simulation software IDA ICE. Nine representative buildings located in Salzburg (Austria) are selected for the comparison, including five single family house (SFH) and four multiple-family house (MFH) with different insulation status[6]. The comparison results are shown in Figure 4. As shown, the FLEX-Operation model approximates the annual heating demand for each building relatively well, which is in accordance with results from Ref [34] and [35]. The biggest difference comes from the building SFH_9B with good insulation.

2.2.2. Heating and Cooling System Modeling

To satisfy the space heating ($\phi_{HC,nd}$) and the exogenous hot water demand, a heating system is included in FLEX-Operation, consisting of (1) a main heater, which can be a heat pump, a fuel-based boiler (natural gas, heating oil, coal, biomass, etc.), or a district heating system; (2) an electric heating element as a backup for peak demand; and (3) two buffer tanks for space heating and domestic hot water, respectively.

When a heat pump is installed as the main heater, we consider its hourly coefficient of performance (COP) depending on the temperatures of the sink (θ^t_{sink}) and source (θ^t_{src}), as calculated by Equation 2.

$$COP^t_{hp} = \eta \times \theta^t_{sink}/(\theta^t_{sink} - \theta^t_{src}) \quad (2)$$

For an air-source heat pump, we assume $\theta^t_{src} = \theta^t_e$ and $\eta = 0.35$. For a ground-source heat pump, we assume $\theta^t_{src} = 10°C$ and $\eta = 0.4$. The η values of the air- and ground-source heat pumps are chosen so that the resulting COP is consistent with the data from the manufacturers [36, 37, 38, 39]. The heat pump size is decided according to the

[6]The buildings SFH_1B, SFH_5B, MFH_1B, MFH_5B are with bad insulation. The buildings SFH_1S, SFH_5S, MFH_1S, MFH_5S are with medium insulation. The building SFH_9B is with good insulation

Table 2
Building parameters in the 5R1C model

Parameter	Explanation	Unit	Value or Equation
A_f	effectively used floor area	m^2	building specific
λ	the ratio between the surface and effective area	1	$\lambda = 4.5$
A_t	the total surface of the building	m^2	$A_t = \lambda A_f$
A_j	the surface area of the building element j	m^2	building specific
k_j	the specific thermal capacity of the building element j	J/Km^2	building specific
C_m	the total thermal capacity of the building mass	J/K	$C_m = \sum_j \left(k_j \times A_j\right)$
A_m	effective mass-related area	m^2	$A_m = C_m^2 / \sum_j \left(k_j^2 \times A_j\right)$
H_{ve}	ventilation transfer coefficient	W/K	building specific
$H_{tr,is}$	surface transfer coefficient	W/K	$H_{tr,is} = 3.45 A_{tot}$
$H_{tr,w}$	window transfer coefficient	W/K	building specific
$H_{tr,ms}$	surface transfer coefficient	W/K	$H_{tr,is} = 9.1 A_m$
H_{tr1}	heat transfer coefficient	W/K	$H_{tr1} = 1/(1/H_{ve} + 1/H_{tr,is})$
H_{tr2}	heat transfer coefficient	W/K	$H_{tr2} = H_{tr1} + H_{tr,w}$
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 specific
H_g	ground heat transmission coefficient	W/K	building specific
H_U	unconditioned room heat transmission coefficient	W/K	building specific
H_A	adjacent buildings heat transmission coefficient	W/K	building specific
H_{op}	transmission coefficient through opaque building elements	W/K	$H_{op} = H_D + H_g + H_U + H_A$
$H_{tr,em}$	effective thermal mass heat transmission coefficient	W/K	$H_{tr,em} = 1/(1/H_{op} + 1/H_{tr,ms})$

peak demand when the environment temperature is $-14°C$. In case of temperature lower than $-14°C$, a supplementary electric heater is added, with $COP = 1$.

Regarding the two buffer tanks for space heating and hot water demand, they are optional in the model. When installed, we assume the temperature inside the tank is homogeneous and the surrounding temperature is $20°C$. The thermodynamic properties of the water - heat capacity (c_{water}), mass (m_{water}), and pressure - are constant. The heat loss coefficients of the tanks equal to $0.2W/m^2K$. The minimum temperature of the tanks equal to $28°C$, based on which a tank's state-of-charge (SOC) is calculated by Equation 3. We assume the space heating tank can be charged up to $45°C$ and $65°C$ for the domestic hot water tank. The heat loss is calculated by Equation 4, with A_{tank} denoting the surface area of the tank. The typical sizes of space heating and domestic hot water tanks are 700L ($A_{tank} = 4.62m^2$) and 300L ($A_{tank} = 2.63m^2$), respectively.

$$Q_{tank,t} = m_{water} \times c_{water} \times (T_{tank,t} - 28) \tag{3}$$

$$Q_{tank\_loss,t} = 0.2 \times A_{tank} \times (T_{tank,t} - 20) \tag{4}$$

Finally, for the space cooling demand, we consider an optional air-conditioner, with constant coefficient of performance equal to 3.

2.2.3. PV and Battery Modeling

FLEX-Operation considers optional PV and battery adoption in the households. The hourly PV generation is exogenous for the model, downloaded from the PV-GIS database[7] for specific regions and years 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. The weights are regional floor areas provided by the HOTMAPS project[8]. For the battery, we assume the charging and discharging

[7] https://re.jrc.ec.europa.eu/pvg_tools/en/
[8] www.hotmaps-project.eu

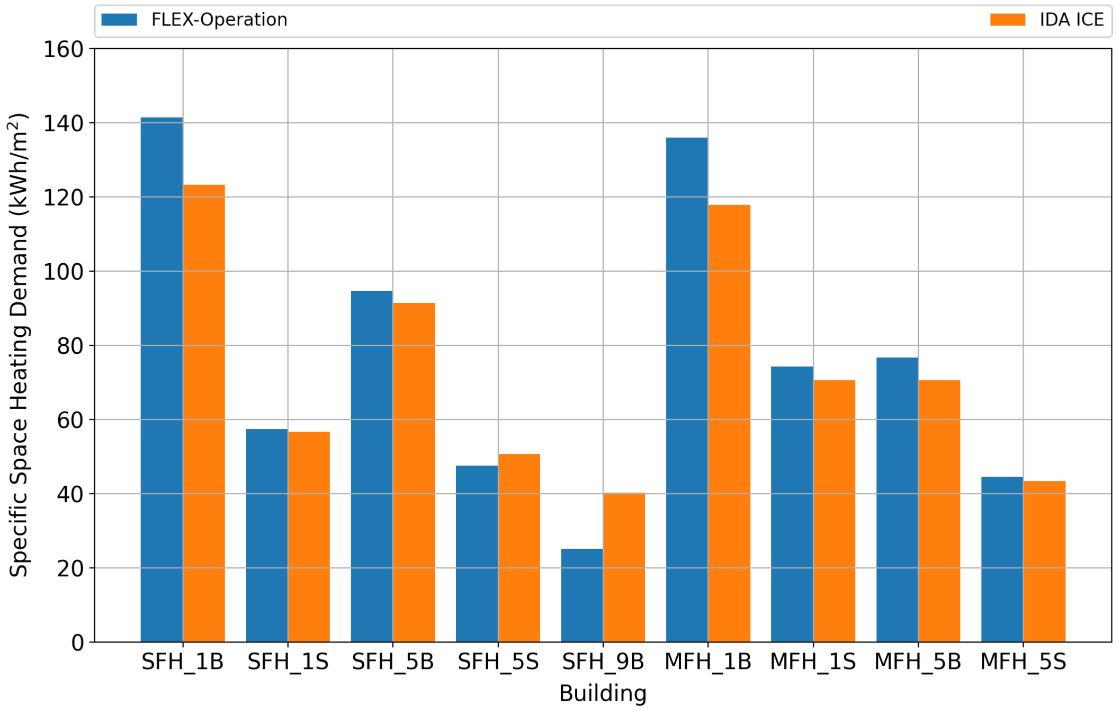


Figure 4: Building heating demand comparison between FLEX-Operation and IDA ICE

efficiency are both 95% with maximum power 4.5kW. The SOC of battery is modeled either following a rule-based apporach or optimized, according to the running mode of the model (see Section 2.2.5).

2.2.4. Vehicle Modeling

As shown in Figure 2, FLEX-Operation also considers an optional vehicle for the household. If included, the driving profile of the vehicle is used as input. It includes two parts:

1. a binary location profile, with ones implying the vehicle is at home and zeros indicating the vehicle is outside.
2. a driving distance profile in the unit of *km*, which is then multiplied with the energy intensity of the vehicle to calculate the final energy demand and cost;

When the vehicle is electric, the model can optimize its charging with the other technologies' operation. This can significantly affect the household's energy system operation: first, if a PV system is available, the EV can be charged with the generation surplus to increase the self-consumption rate of PV; second, under dynamic electricity prices, the EV can be smartly charged from the grid when the electricity price is lower with SEMS installation.

2.2.5. Running Modes

For a household/building with all the above-mentioned technologies configured, FLEX-Operation can calculate the hourly operation of its energy system in three modes: (1) simulation, (2) perfect-forecasting optimization, and (3) rolling-horizon optimization.

First, in the *simulation* mode, the model follows a rule-based approach: (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; and (3) if there is still PV generation left, it is sold to the grid.

Second, in the *perfect-forecasting optimization* mode, the model optimizes the hourly operation of all installed technologies to minimize the total energy cost through the whole year, assuming the electricity price and weather are all known from the beginning. The objective function is shown by Equation 5, assuming heating and vehicle are both electric for simplicity. EP_t and FiT_t represent the electricity price and PV feed-in tariff, respectively. The total electricity consumption from the grid ($EC_{grid,t}$) includes all internal loads from appliances ($EC_{app,t}$), heating system ($EC_{hs,t}$), cooling system ($EC_{cs,t}$), electric vehicle ($EC_{ev,t}$), and SOC change of battery ($EC_{bat,t}$). Then, the consumption supported by PV-generation ($ES_{pv2load,t}$) is deducted (equation 6). Besides, the PV-generation ($ES_{pv,t}$) can be used to support internal loads, battery, EV, and if still remains, the surplus will be sold to the grid (Equation 7).

$$\min \quad Cost = \sum_{t=1}^{8760}(EP_t \times EC_{grid,t} - FiT_t \times ES_{pv2grid,t}) \tag{5}$$

$$EC_{grid,t} = EC_{app,t} + EC_{hs,t} + EC_{cs,t} + EC_{ev,t} + EC_{bat,t} - ES_{pv2load,t} \tag{6}$$

$$ES_{pv,t} = ES_{pv2load,t} + ES_{pv2bat,t} + ES_{pv2ev,t} + ES_{pv2grid,t} \tag{7}$$

In the optimization, the building can be pre-heated to minimize the total energy cost, which can be reflected by the hourly heating demand profile. So, we conducted the comparison between FLEX-Operation with IDA ICE again for two buildings shown in Figure 4: (1) SFH_9B where IDA ICE demand is higher, and (2) SFH_1B where FLEX-Operation demand is higher. The hourly indoor temperature result from FLEX-Operation is used as input for IDA ICE to parametrize the "set temperature", then compared with the indoor temperature calculated by IDA ICE, as shown in Figure 5 (left). As IDA ICE is not an optimization model — the "set temperature" works as a direction instead of constraint — the orange profile follows the blue one closely but not exactly. Besides, Figure 5 (right) shows the hourly heating demand in FLEX-Operation and IDA ICE for the two buildings, in which FLEX-Operation is shown to underestimate the heating demand (heat loss) for SFH_9B with higher efficiency and overestimate for SFH_1B with lower efficiency. Finally, the less efficient SFH_1B has less number of peaks than SFH_9B because it has higher losses after being pre-heated in the optimization, so it is not as frequently pre-heated as the more efficient SFH_9B by the optimization. This also indicates that buildings with higher efficiency have higher flexibility for heat load shifting.

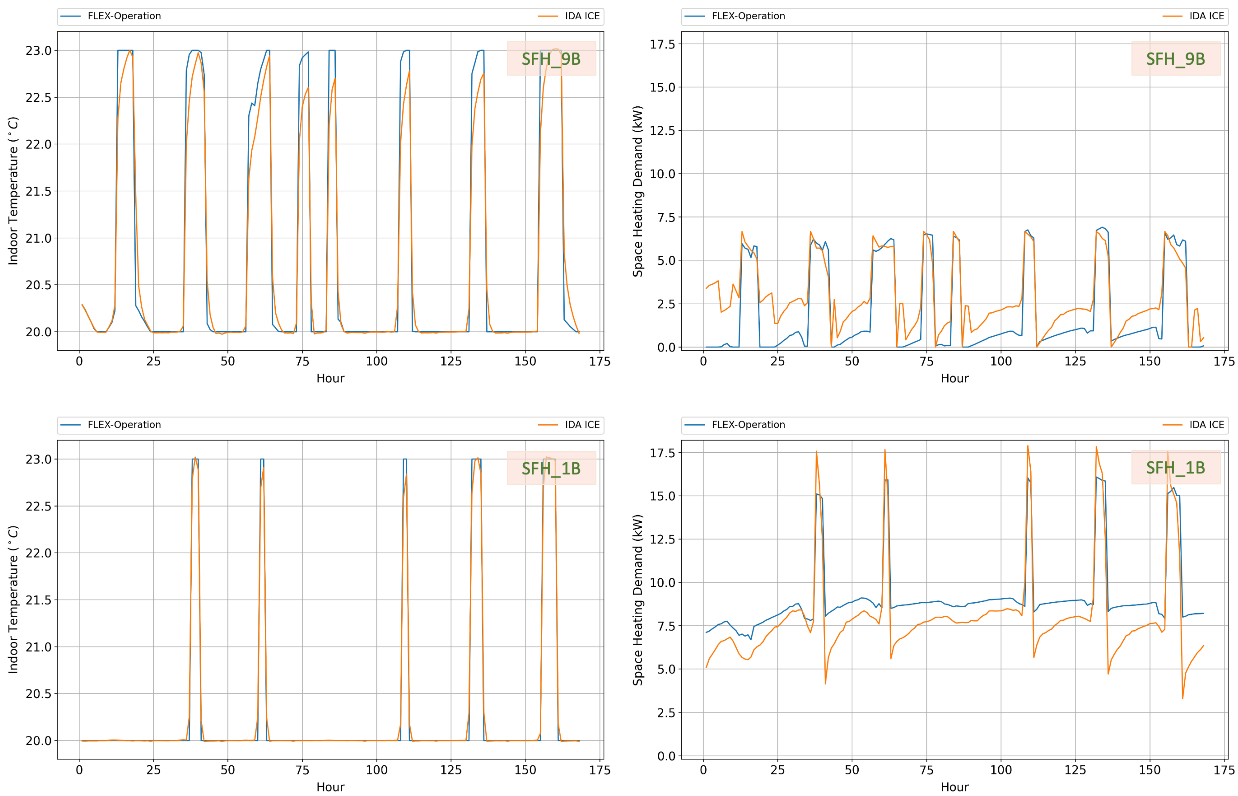


Figure 5: Comparison between FLEX-Operation and IDA ICE: indoor temperature (left) and heating demand (right)

Third, in the *rolling-horizon optimization* mode, the model optimizes the hourly operation of technologies to minimize the total energy cost, but in rolling time windows recursively instead of through the whole year. The other settings are same with the perfect-forecasting optimization mode. As shown in Figure 6, the time window for Day N starts at 12:00 and the optimization horizon is 36 hours, based on the forecasts of electricity price, environment temperature, and radiation. Then, only the results in the first 24 hours are kept and the optimization starts again at 12:00 on Day $N + 1$.

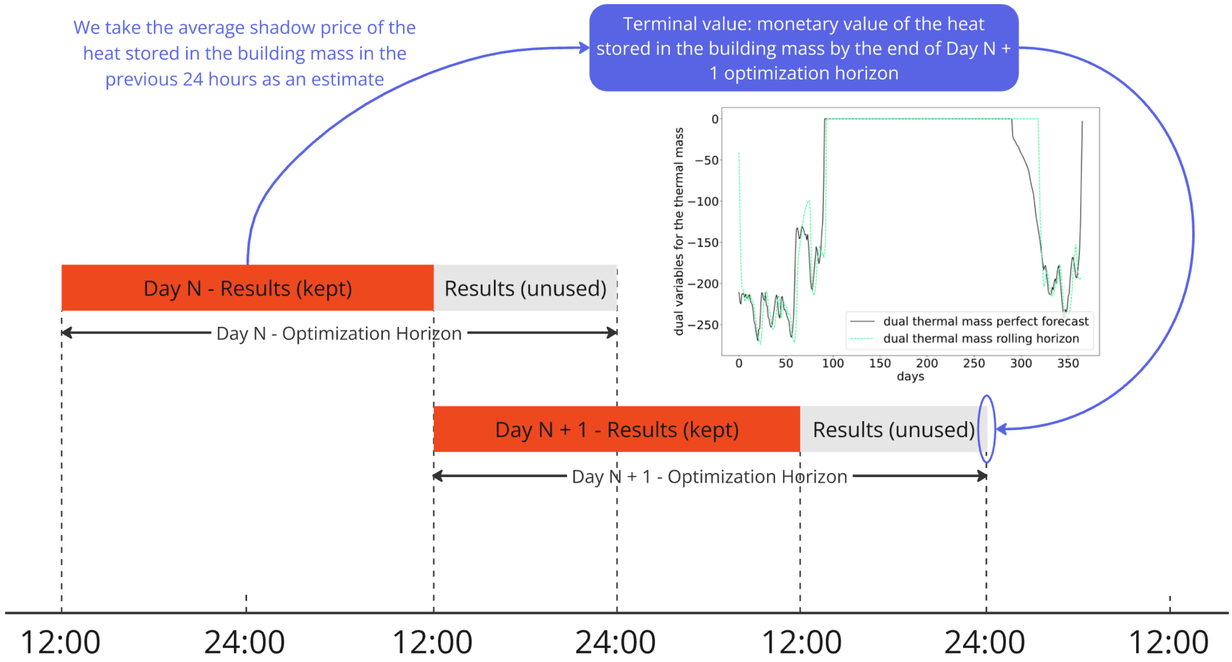


Figure 6: Optimization timeframe of the rolling-horizon optimization mode in FLEX-Operation

We designed it in this way because the electricity price forecasts are updated at 12:00 every day and weather forecasts within 36 hours are also more reliable. Besides, according to the literature, having a longer optimization horizon improves the effectiveness of the optimization. However, since the horizon of 36 hours is too small to adequately take the inertia of the building mass into account, we also considered the impact of "terminal value", which refers to the monetary value of the heat stored in the building mass by the end of each time window. In the literature, this is also referred to as "cost to go" [40] or "terminal cost" [41] of a storage. As far as we are aware of, there is no study applying rolling-horizon optimization to single buildings with terminal value considered yet. We try to cover this by taking the average shadow price of the heat stored in the building mass in the previous 24 hours as an estimate. Figure 6 shows the dual variables of the terminal value in rolling-horizon optimization and the average shadow price in perfect-forecasting optimization.

Finally, Figure 7 shows the annual energy cost of the nine representative buildings by running the three modes. To focus on the impact of building mass and its terminal value, we removed the PV, battery, and water tanks. As a result, the cost saving impact of SEMS on such buildings are limited, ranging from 0.39% to 0.71% for the rolling-horizon mode and 0.83% to 1.5% for the perfect-forecasting mode. Additionally, we found that considering the "terminal value" in the rolling-horizon mode can be important, as it contributes 23.67% to 75.00% of the cost saving in this mode. One thing to note is that, these costs are calculated with the electricity price in Austria in 2019. An increase of the price volatility will also increase the cost-saving in the two optimization modes.

2.3. FLEX-Community

FLEX-Community models an energy community consisting of households with heterogeneous behaviors, building envelopes, and technology adoptions. Receiving the results of individual households calculated in FLEX-Operation, the FLEX-Community model has a more detailed capture of the community members than the existing models in the literature. Taking the perspective of an aggregator of the community, the model 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 options support the aggregator's business model.

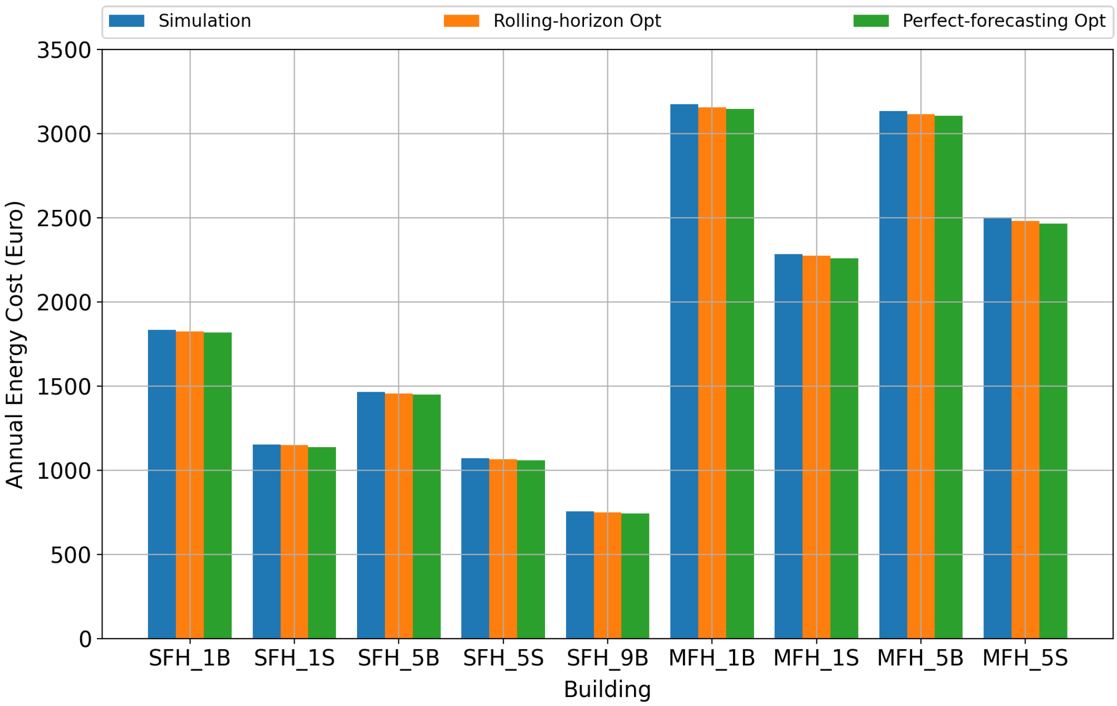


Figure 7: Annual energy cost comparison between the three running modes

First, due to the heterogeneity among households, in some hours, some households with PV sell their surplus generation to the grid at the lower feed-in tariff, while some other households buy electricity from the grid at a higher price. With an aggregator managing the community, they can trade electricity with each other. As a result, the aggregator can facilitate such trading by (1) buying the electricity at a price ($P_t^{bid} = \theta^{bid} FIT_t$) not lower than the feed-in tariff ($\theta^{bid} \geq 1$), and (2) selling the electricity at a price ($P_t^{ask} = \theta^{ask} P_t$) not higher than the grid price ($\theta^{ask} \leq 1$). From those hours when P_t^{ask} is higher than P_t^{bid}, the aggregator can earn the profit π^{p2p} as calculated by Equation 8.

$$\pi^{p2p} = \sum_{t=1}^{8760} (P_t^{ask} - P_t^{bid}) Q_t \tag{8}$$

Second, apart from facilitating P2P trading in real-time, the aggregator can also buy electricity at a lower price and sell it later when the price is higher. This requires the aggregator to control a battery, which can include two parts: a self-owned battery and the remaining battery capacity of the community members. As a result, by optimizing the battery operation, the aggregator can earn the profit π^{opt}. The larger the battery capacity is, the higher π^{opt} the aggregator can earn.

3. Results

To demonstrate the capabilities of the FLEX modeling suite, we defined five representative households (HH 1-5) from Germany composed of different members, based on the four person types supported in FLEX-Behavior, as listed in Table 3. Taking the household composition as input, FLEX-Behavior calculates the activity profile for the each household member, then converts the activity profiles to their energy demand profiles of appliance electricity and hot water, as well as their building occupancy profiles. Then, these profiles are aggregated to the household level for each of HH 1-5, as shown in Figure 8. The annual results are summarized in Table 4.

As shown, except for HH5, the appliance electricity demand increases with the number of household members, but the marginal increment declines, implying shared use of some appliances, e.g., lighting, refrigerator, etc. Besides, the HH5 has a different shape of appliance electricity demand (i.e., peaking around noon), due to the use of cooking and housework appliances. Finally, the annual occupancy hours of the households range between 5347 to 8291, implying

Table 3
Representative households

ID	Fully-employed Adult	Partly-employed Adult	Student	Retired Person
HH1	1	0	0	0
HH2	2	0	0	0
HH3	2	0	1	0
HH4	1	1	2	0
HH5	0	0	0	2

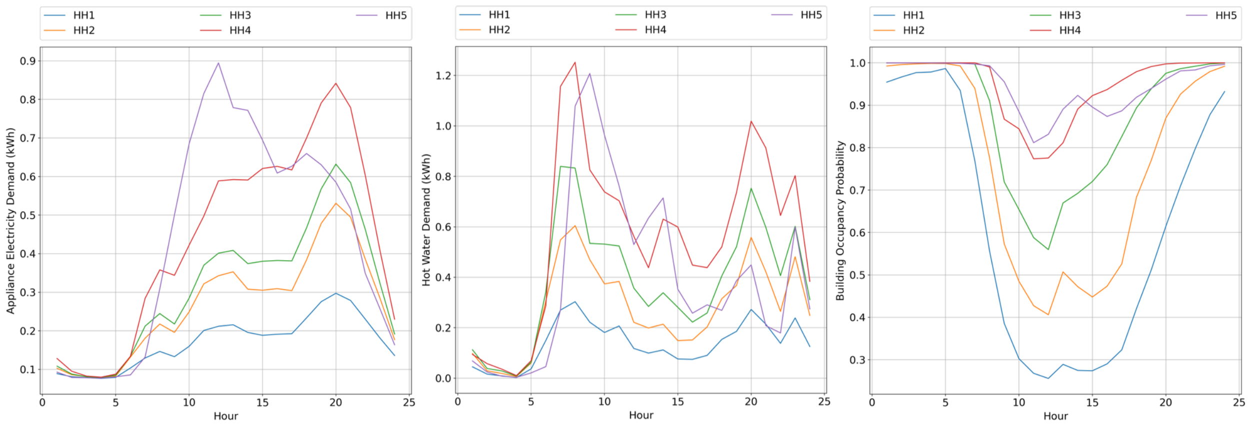


Figure 8: Average appliance electricity demand, hot water demand, and building occupancy profiles of HH 1-5

Table 4
Annual energy demand and building occupancy

ID	Appliance Electricity [kWh]	Hot Water [kWh]	Occupancy [h]
HH1	1499	1220	5347
HH2	2331	2444	6638
HH3	2724	3357	7622
HH4	3834	4879	8300
HH5	3823	3504	8291

a higher energy-saving potential of SEMS for younger and smaller households, because the heating and cooling can be turned off when they are outside during the day.

Taking the profiles of HH3 calculated with FLEX-Behavior, we apply the FLEX-Operation model to calculate the household's energy system operation. We assume the household lives in a moderate efficient building heated by an air-source heat pump and cooled by an air-conditioner. There are also installations of PV and battery. Besides, we assume that the maximum and minimum temperatures for the household are $27°C$ and $20°C$ no matter if the building is occupied or not. Finally, we consider hourly dynamic electricity prices between 0.21 and 0.42 Euro/kWh and constant PV feed-in price at 0.07 Euro/kWh. The hourly environment temperature for Germany is developed following the same approach with PV generation (see Section 2.2.3) based on the PV-GIS data.

Figure 9 shows the electricity balance of the household in summer (top) and winter (bottom) weeks. The impact of SEMS is reflected by running the model in the "(perfect-forecasting) optimization" mode[9], taking the "simulation"

[9]For simplicity, we present only the results from the perfect-forecasting optimization mode, as the difference between the two optimization modes are limited and we don't focus on a detailed comparison of the two here.

results as a benchmark. The end-uses of electricity are represented by "positive" bars in different colors, while the "negative" bars show how the electricity demand is supplied in each hour, for example, by the grid, PV generation, or battery discharge. Besides, the feed-in of PV to the grid is also represented by "negative" bars in pink color.

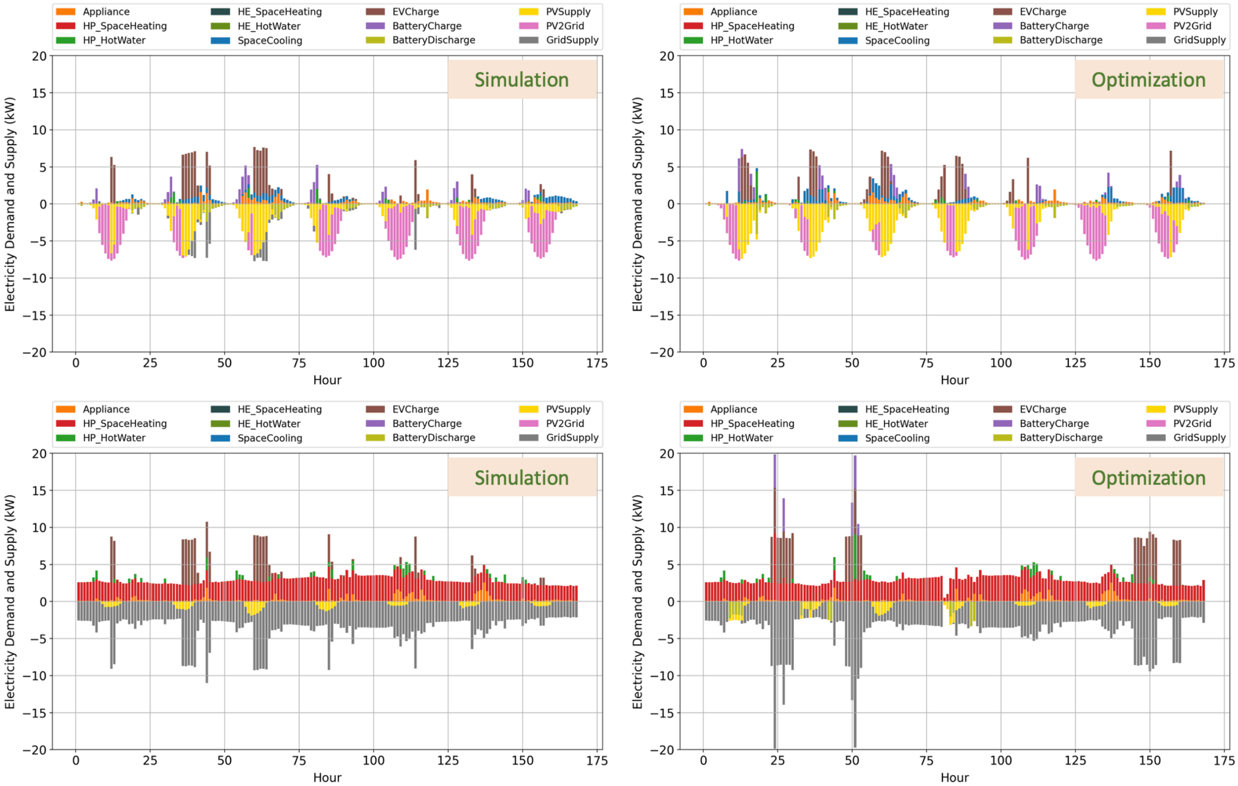


Figure 9: Electricity balance of HH3 in summer (top) and winter (bottom) weeks

As shown, in a summer week, most of the household's electricity demand can be satisfied by its PV and battery system, no matter if SEMS is adopted. However, when the battery operation can be optimized by an SEMS, its charging time will be postponed to around noon, as well as the domestic hot water tank. The PV surplus in the morning will be sold to the grid. The space cooling demand is also impacted by the building mass being used as storage. In a winter week, the PV generation is reduced. The household cannot sell PV surplus to the grid and the use of battery is also limited. The battery is only used when SEMS is adopted: the household can optimize by charging the space heating tank and the battery when the electricity price is lower, so we observe higher peaks around hours 25, 50, etc.

Finally, by varying the households' behavior profiles and the component assumptions, 640 heterogeneous households are constructed among which 320 of them are with PV installations. We assume that these households do not have SEMS installed by themselves but are members of an energy community. Their energy system operation is first calculated by the FLEX-Operation model with the simulation mode and then fed into the FLEX-Community model.

Figure 10 shows the electricity balance of the community as a whole in summer and winter weeks. So, with half of the household installed PV, the community can be a net electricity producer in some hours while being a net consumer in the other hours in the summer. This means the aggregator can make a profit by shifting the surplus generation. Besides, under dynamic electricity price, the aggregator can store electricity when the price is lower and sell it when the price is higher. Finally, due to the heterogeneity within the community, the aggregator can also facilitate real-time P2P trading within the community. As a result, Figure 11 shows the strategy optimized for the aggregator: P2P electricity trading amount and battery charge/discharge in each month of the year.

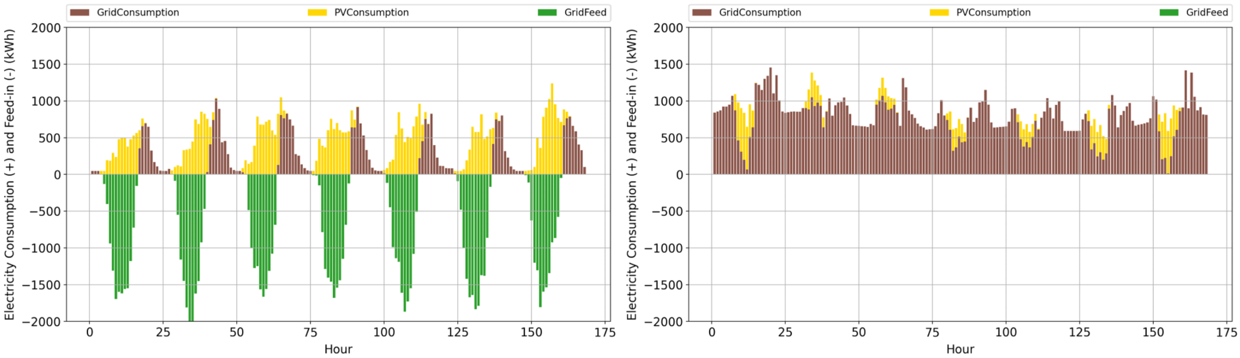


Figure 10: Electricity balance of the energy community (50% PV adoption) in summer (left) and winter (right) weeks

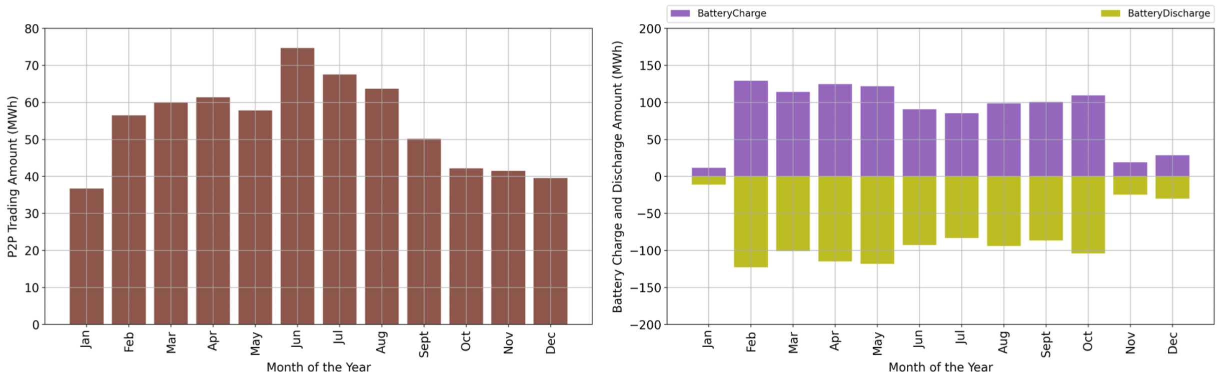


Figure 11: P2P electricity trading amount and battery charge/discharge in the community

4. Discussions

By integrating three models into a consistent framework, FLEX provides the flexibility to analyze household energy consumption and impact of various technologies at different scales. In FLEX-Behavior, users can specify the composition of one household and analyze its appliance electricity and hot water demand, as well as the building occupancy. Assumptions of teleworking can be applied. By using FLEX-Operation, the counterfactual impact of different technology installations can be analyzed by comparing the results of different setups. For example, in Ref [42], FLEX-Operation is used to assess how smart charging can impact the cost of owning electric vehicles. At the national level, FLEX-Operation has also been used to analyze the impact of smart energy management [13], variable electricity price [14], and the potential of decentral heat pumps as flexibility option for decarbonised energy systems [43]. Finally, by taking results from the first two models, FLEX-Community significantly improves the level of details in the modeling of energy communities. Users can construct an energy community from scratch, by defining the household composition and behavior of each community member, as well as their adoptions of HP, PV, battery and EV in detail.

Despite its modeling flexibility, the FLEX suite also faces several limitations.

- First, the current version of FLEX-Behavior is based on the time-use survey data from Germany collected in 2012-2013, limiting its applicability to other countries. The model will also require updates when the micro-level data from the latest survey becomes available. Then, the profiles of electricity and hot water demand, as well as building occupancy, should be also validated again with more detailed empirical data, preferably from the typical households categorized by socio-demographic properties.

- Second, FLEX-Behavior only models the profiles of appliance electricity demand, hot water demand, and building occupancy. These may be inconsistent with the driving profiles used in FLEX-Operation. We acknowledge the approach in Ref [5], where the authors generate all four profiles together. Users may also link that model with FLEX-Operation if necessary. Besides, for households with multiple members sharing a single EV, the uncertainty in EV driving behavior could be significant, which may reduce the impact of these inconsistencies. Moreover, in Ref [42], we use driving profiles developed from MOP[10] data, which has a longer observation period, offering better insights into daily driving patterns compared to MiD[11] data used in Ref [5].

- Third, FLEX-Operation focuses only on the operational costs of a household's energy system. For users interested in determining the optimal size of PV systems or batteries, the model requires running simulations for various size combinations and then processing the results manually. This involves adding the investment costs separately to compare the overall system economics. Integrating size optimization for PV and battery into FLEX-Operation is on our research agenda for the next phase.

- Fourth, FLEX-Community is designed from the perspective of an aggregator, optimizing its strategies for facilitating peer-to-peer trading and operating batteries. However, this approach may not be applicable to energy communities that operate without an aggregator. The model could be enhanced to include mechanisms for decentralized energy communities.

5. Conclusions

Technological advancements and changing behaviors are reshaping household energy consumption patterns, necessitating more advanced models to quantify their impacts on energy demand and inform effective policy-making. In response, this paper introduces the open-source FLEX modeling suite, which integrates households' behavior, energy system operation, and interactions within energy communities into a consistent framework. As a result, detailed assumptions about households' behavior and technology adoption are carried through to the modeling of their interactions within an energy community. The framework provides flexibility for incorporating diverse household characteristics and varying technology configurations, making it adaptable to different scenarios and scales of analysis.

CRediT authorship contribution statement

Songmin Yu: conceptualization, methodology (FLEX-Behavior/Operation/Community), writing the first draft, data development, review and editing. **Philipp Mascherbauer:** conceptualization, methodology (FLEX-Operation), writing the first draft, data development, review and editing. **Thomas Haupt:** methodology (FLEX-Operation), data development, review. **Kevan Skorna:** methodology (FLEX-Behavior), data development, review. **Hannah Rickmann:** methodology (FLEX-Behavior), visualization, review. **Maksymilian Kochanski:** data development, visualization, review. **Lukas Kranzl:** conceptualization, review, grant application, supervision, project management.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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