FLEX: a Modeling Suite for Households' Behavior, Energy System Operation, and Interaction in the Energy Community*

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ABSTRACT

The interplay between technological and behavioral changes are unfolding within the household sector. After adopting the photovoltaic systems, "prosumers" can further evolve into "prosumagers", by actively managing energy storage with smart systems. Moreover, influenced by the COVID-19 shock, people are also redefining their work-life balance and embracing teleworking. These changes introduce complexities to the energy transition and necessitate improved modeling. In this regard, this paper presents FLEX, an open-source modeling suite for households' behavior, energy system operation, and interactions in the energy community. FLEX includes three linked models. First is FLEX-Behavior, which models the hourly behavior and energy demand profiles of representative households, based on a time-dependent Markov core estimated for different person- and day-types with Time-use Survey data. Second, FLEX-Operation focuses on the energy system operation of households, whose building envelope and technologies can be configured in detail, including heating systems, photovoltaic, thermal and battery storage, electric vehicles, and smart energy management systems. Third, taking the results from FLEX-Operation as input, households' interaction in an energy community is modeled by FLEX-Community from the perspective of an aggregator, who optimizes its profit by (1) facilitating peer-to-peer electricity trading, and (2) optimizing the operation of batteries in the community. In summary, FLEX facilitates the analysis of representative households and their interaction. The counterfactual impact of technology and behavioral change can be analyzed. Furthermore, by aggregating the results to the national level, FLEX can also support power system analysis. Illustrative results are presented to demonstrate FLEX's capabilities and limitations.

1. Introduction

Combining heat pumps (HP), photovoltaic (PV), energy storage, and smart energy management systems (SEMS) contributes to a carbon-neutral household sector three-fold. First, the heat supply can be decarbonized with electricity. Second, with HP installation, households receive stronger motivation to adopt PV systems, i.e., more distributed renewable generation. Third, households' energy storage and SEMS can provide flexibility to balance the fluctuations from the supply side. The energy storage can be (1) battery storage installed at home or in an electric vehicle (EV), and (2) thermal storage (including building mass and hot water tank), especially when the installed HP can be smartly controlled under dynamic electricity prices. Apart from the technology system, household behaviors can also play an important role in the transition, e.g., (1) the impact of teleworking on building occupancy and heating/cooling demand, (2) the driving behavior of EVs and the interactions with other technologies, (3) the development of an "energy community" in which end-users can trade electricity with each other or through an "aggregator".

We developed the FLEX modeling suite to capture these 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. 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

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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 both simulation and optimization modes, with the latter minimizing the energy cost and representing the use of SEMS.

- 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 the following 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 interaction 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 cost 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 reviews the studies on modeling the three parts covered in FLEX. Then, we introduce the three models in FLEX in Section 3, followed by the exemplary results in Section 4. Finally, we discuss the potential applications and limitations of the modeling suite and conclude in Section 5.

2. Literature Review

The modeling of households' energy consumption starts from the modeling of households' behavior, including occupant status (e.g., absence, presence, number of occupants, etc.), energy behaviors, and behavioral efficiency (Chen, Zhang, Xia, Chen, Setunge and Shi, 2021). Especially, many studies focus on the impact of occupants' behavior on the electric load profiles. With more and more micro-data available, studies have switched from the top-down approaches (Aigner, Sorooshian and Kerwin, 1984; Bartels, Fiebig, Garben and Lumsdaine, 1992) to the bottom-up simulation. In this context, Widén and Wäckelgård (2010) 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. Müller, Biedenbach and Reinhard (2020) improved the approach by (1) considering activities' time-dependent "duration" probabilities, and (2) covering the profiles of hot water demand and driving. Regarding the empirical evidence, Osman and Ouf (2021) presented a comprehensive review of the available TUS datasets, modeling methods, and implementations in building energy research.

Taking the energy demand and occupancy profiles from the behavior models as input, household energy system models focus on the operation of a building's energy system as well as 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, including 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 an individual 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, which makes it possible to integrate them into an optimization algorithm. Sperber, Frey and Bertsch (2020) compared different RC models and showed that the 5R1C approach (DIN ISO 13790[4]) can balance the details of building modeling and the computation demand of optimization. This approach has also been tested and compared to more sophisticated models in various studies (Bruno, Pizzuti and Arcuri, 2016; Michalak, 2014).

Several studies combined the building modeling with other energy consumption and technologies (incl. hot water, electric appliances, PV and battery, and EV) in an optimization framework. The objectives include the minimization of energy cost (Kandler, 2017; Mascherbauer, Kranzl, Yu and Haupt, 2022a; Mascherbauer, Schöniger, Kranzl and Yu, 2022b), maximization of the self-consumption rate of a PV system (Klingler, 2018), and peak reduction (Kippelt, 2018). 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. Haupt (2021) summarized the recent modeling studies and their coverage of the major components.

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

[1] Transient System Simulation Tool: https://www.trnsys.com/.

[2] EnergyPlus: https://energyplus.net/.

[3] IDA Indoor Climate and Energy: 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.

markets. Reasons for participating in a community are decreasing energy costs and addressing climate change, as well as the community spirit (Dóci, Vasileiadou and Petersen, 2015).

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 (Ali, Alahäivälä, Malik, Humayun, Safdarian and Lehtonen, 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). Özge Okur, Heijnen and Lukszo (2021) reviewed the business models 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 the micro-grid level (Gruber, Bachhiesl and Wogrin, 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 member. Koirala, Koliou, Friege, Hakvoort and Herder (2016) compared different options to integrate energy systems into an energy community (e.g., community microgrids, virtual power plants, energy hubs, prosumer community groups, etc.). Huang, Lovati, Shen, Chai and Zhang (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.

Given all the possible options, PV systems are the most established (Hirschburger and Weidlich, 2020) and of particular interest to energy communities. Fina, Auer and Friedl (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 further increased and the peak demands can be shaved even more (Roberts, Bruce and MacGill, 2019). 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, Mahmoudi, Heydarian-Forushani, Shafie-khah, Saha, Golshan and Siano (2017) 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 Han, Alston and Gillott (2022), the increased peak demand of an electrified heating network can be substantially reduced by employing an energy community. Compared with the studies focusing on individual households, the households in the community modeling are significantly simplified to reduce the scale of the optimization problem. For example, Özge Okur, Voulis, Heijnen and Lukszo (2019) 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.

In summary, models have been developed for households' behavior, energy system operation, and energy communities. However, a comprehensive framework that integrates all three aspects is currently lacking. Specifically, in the context of energy communities, the modeling of individual households tends to be simplified, neglecting their technological and behavioral heterogeneity and the consequent impact.

3. Model

FLEX is a modeling suite that covers households' energy consumption in a consistent framework from behavior to their interactions in an energy community. The behaviors and energy demand profiles of individual occupants in a household are modeled in the FLEX-Behavior model (Section 3.1), which are aggregated to the household level and serve as the input for the FLEX-Operation (Section 3.2) model. Then, the operation of the household's energy system can be calculated in both optimization and simulation modes. Finally, taking the results of a group of households calculated in the FLEX-Operation model, the FLEX-Community models their interaction in an energy community from an aggregator's perspective. The P2P electricity trading and the operation of batteries in the community are optimized (Section 3.3).

3.1. 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 data from Germany.

Every decade, the Federal Statistical Office in Germany conducts a large-scale, representative survey to record the time-use of its citizens. The most recent published survey (also used in this study) was conducted from August 2012 to July 2013. 5040 households, composed of over 12000 individuals, participated 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). The diaries 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

Table 1
Reclassified activity categories

ID	Activity Category	Related Appliances
1	Sleeping	No appliance.
2	Eating and drinking	No appliance.
3	Hygiene and dressing	Hot water, toothbrush, shaver, hair dryer, and hair iron.
4	Meal preparation	stove, oven, microwave, pressure cooker, sandwich maker, toaster, blender mixer, water kettle, and coffee machine.
5	Dish washing	Dishwasher and hot water.
6	Cleaning home	Hot water and vacuum cleaner.
7	Doing laundry	Washing machine and dryer.
8	Ironing and maintaining clothes	Electric iron and sewing machine.
9	Entertainment	Computer, laptop, tablet, mobile phone, television, projector, game console, and speaker amplifier.
10	Other activities at home	No appliance.
11	Working	computer, laptop, tablet, mobile phone, and printer.
12	Education	computer, laptop, tablet, mobile phone, and printer.
13	Other activities outside of home and sports	No appliance.
14	Other journey	No appliance.
15	Commuting to work or study	No appliance.
16	Maintenance work at home	Lawnmower and electric power tools.
17	Taking a break during work or school	Mobile phone, microwave, sandwich maker, toaster, water kettle, and coffee machine.

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 (1) fully-employed adults (age between 20 to 65); (2) partly-employed adults (age between 20 to 65); (3) students (younger than 20), and (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: (1) weekday (from Monday to Friday); and (2) weekend (Saturday and Sunday).

For each representative person, FLEX-Behavior generates the activity profile in 10-minute resolution for a year, i.e., 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, e.g., "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 Equation 1, i.e., the Markov matrix. $\boldsymbol{P}$ 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 ($t \geq 2$).

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

- Third, after switching to the new activity, the model will draw its duration from the distribution again.

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.

Taking the generated activity profile as an intermediate result, FLEX-Behavior further 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 predefined probabilities. Finally, we combine the assumption of "teleworking" with the generated profiles. If a person is "teleworking" on a specific day, the activities "working" and

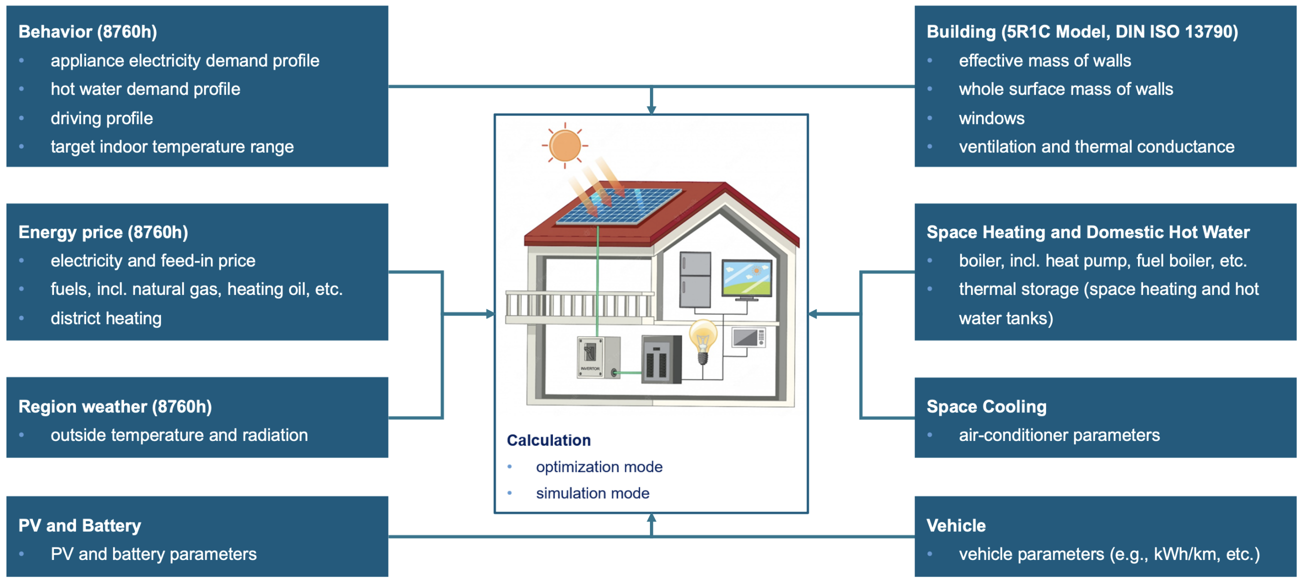

Figure 1: Structure of the FLEX-Operation model

"taking a break during 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.

3.2. FLEX-Operation

FLEX-Operation models the hourly operation of a household's energy system considering five energy services: (1) electric appliances (e.g., lighting, television, refrigerator, etc.), (2) domestic hot water, (3) space heating, (4) space cooling, and (5) vehicle.

Figure 1 shows the model structure. 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. To include the impact of a potential electric vehicle, FLEX-Operation can also take a driving profile as input, i.e., the driving distance in each hour of the year, as well as a binary location array representing the vehicle being at home or outside.

Given the target indoor temperature range and the outside temperature, the building's heating and cooling demand is modeled with the 5R1C approach following DIN ISO 13790. As shown in Figure 2, a building is represented by a circuit with five resistances and one capacity. The related parameters are summarized in Table 2. The relation between outside temperature (θ_{out}), indoor temperature (θ_{air}), and heating&cooling demand (ϕ_{HC}) is calculated by Equation 2, with ϕ representing the heat flows (unit: W) and θ representing the temperatures (unit: $°C$). The node temperature θ^t_s is calculated with Equation 3, in which $\theta^t_{m\_avg}$ represents the average temperature of the building mass in the previous and current hour and is calculated by the Equations 4-8.

$$\theta_{air} = \frac{H_{is}\theta^t_s + H_{ve}\theta^t_{out} + \phi_{ia} + \phi^t_{HC}}{H_{is} + H_{ve}} \tag{2}$$

$$\theta^t_s = \frac{H_{ms}\theta^t_{m\_avg} + \phi^t_{st} + H_w\theta^t_{out} + H_{tr1}[\theta^t_{out} + \frac{\phi_{ia}+\phi^t_{HC}}{H_{ve}}]}{H_{ms} + H_w + H_{tr1}} \tag{3}$$

$$\theta^t_{m\_avg} = \frac{(\theta^t_m + \theta^{t-1}_m)}{2} \tag{4}$$

$$\theta^t_m = \frac{\theta^{t-1}_m[C_m/3600 - 0.5(H_{tr3} + H_{em})] + \phi^t_{m\_tot}}{C_m/3600 + 0.5(H_{tr3} + H_{em})} \tag{5}$$

$$\begin{aligned} \phi^t_{m\_tot} &= \phi^t_m + H_{em}\theta^t_{out} + H_{tr3}\phi^t_{st} + H_{tr3}H_w\theta^t_{out} \\ &+ \frac{H_{tr3}H_{tr1}}{H_{tr2}}(\frac{\phi_{ia} + \phi^t_{HC}}{H_{ve}} + \theta^t_{out}) \end{aligned} \tag{6}$$

$$\phi^t_{st} = (1 - \frac{A_m}{A_t} - \frac{H_w}{9.1A_t})(0.5\phi_{int} + \phi^t_{sol}) \tag{7}$$

$$\phi^t_m = \frac{A_m}{A_t}(0.5\phi_{int} + \phi^t_{sol}) \tag{8}$$

Following this 5R1C approach, the building mass is considered as thermal storage in the calculation. We use this reduced-order representation of a building rather than other more detailed ones to reduce the computational demand, especially when optimizing the system operation with all the technologies installed in the building.

To satisfy the space heating and the exogenous hot water demand, a heating system is included in FLEX-Operation, consisting of (1) a main boiler, which can be a heat pump,

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_{tot}	the total surface of the building	m^2	$A_{tot} = \lambda A_f$
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	$H_{tr2} = H_{tr1} + H_w$
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	$H_{tr,em} = 1/(1/H_{op} + 1/H_{tr,ms})$

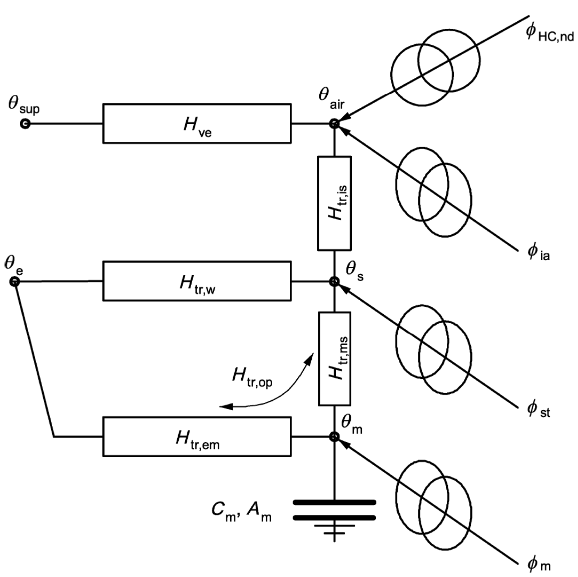

Figure 2: 5R1C circuit representation of a building

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 ($45°C$) and domestic hot water ($65°C$), respectively. When an air-source heat pump is installed, we consider its hourly coefficient of performance (COP) depending on the temperatures of the tank (T^t_{tank}) and source ($T^t_{src} = T^t_{out}$), as calculated by Equation 9, with $\eta = 0.35$. For a ground-source heat pump, we assume $T^t_{src} = 10°C$ and $\eta = 0.4$. Finally, for the space cooling demand, we consider the optional adoption of an air-conditioner, with a coefficient of performance equal to 3.

$$COP^t_{hp} = \eta \times \frac{T^t_{tank}}{T^t_{tank} - T^t_{src}} \tag{9}$$

Regarding the green technologies of households, FLEX-Operation considers PV, battery, and EV. The hourly PV generation is downloaded from the PVGIS database[5] 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[6] as weights. A similar approach is also applied to prepare the hourly outside temperature data downloaded from the PVGIS database.

Finally, FLEX-Operation considers two modes of calculation: 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 to

[5] https://re.jrc.ec.europa.eu/pvg_tools/en/

[6] The regional floor area information is taken from the HOTMAPS project: www.hotmaps-project.eu.

minimize the total annual energy cost. 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; and (3) if there is still PV generation left, it is sold to the grid.

3.3. 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.

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 10.

$$\pi^{p2p} = \sum_{t=1}^{8760} (P_t^{ask} - P_t^{bid}) Q_t \tag{10}$$

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.

4. Case Study

In this section, we present the results of a case study for Germany to demonstrate the capabilities of FLEX. First, in Section 4.1, FLEX-Behavior is applied to calculate the energy demand and building occupancy profiles of five representative households. Then, taking the calculated "behavior profiles" as input, the FLEX-Operation model calculates the energy system operation for a set of households, each configured with different behaviors, building envelopes, and technology adoptions. The detailed results of one household are presented in Section 4.2. Finally, FLEX-Community is applied to calculate the operation of an energy community consisting of the pre-calculated households. The results are presented in Section 4.3.

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

4.1. FLEX-Behavior

Based on the four person types in FLEX-Behavior, five representative households (HH 1-5) composed of different members are defined and listed in Table 3. Then, the calculation is conducted as follows.

First, for each household, the activity profile of each member is generated in 10-minute resolution throughout the year. Figure 3 shows an example of the activity pattern of a fully-employed adult on weekdays, comparing the TUS data (left) and model results (right).

Second, household members' activity profiles are converted to energy demand and building occupancy profiles and then aggregated to the household level. The daily average profiles of the households are presented in Figure 4-6. The annual results are summarized in Table 4.

For each household, the annual appliance electricity and hot water demand are calibrated to Destatis (2022). 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 a higher energy-saving potential of SEMS for younger and smaller households: heating and cooling should be turned off when the people are outside.

4.2. FLEX-Operation

Taking the profiles of HH3 calculated with FLEX-Behavior, we apply the FLEX-Operation model to calculate the household's energy system operation. Further assumptions are made on the household's building and technology adoptions, as listed in Table 5. Besides, we assume that the set temperatures for the household are 27°C and 20°C when the building is occupied or not, respectively. Finally, we consider hourly dynamic electricity prices between 0.21

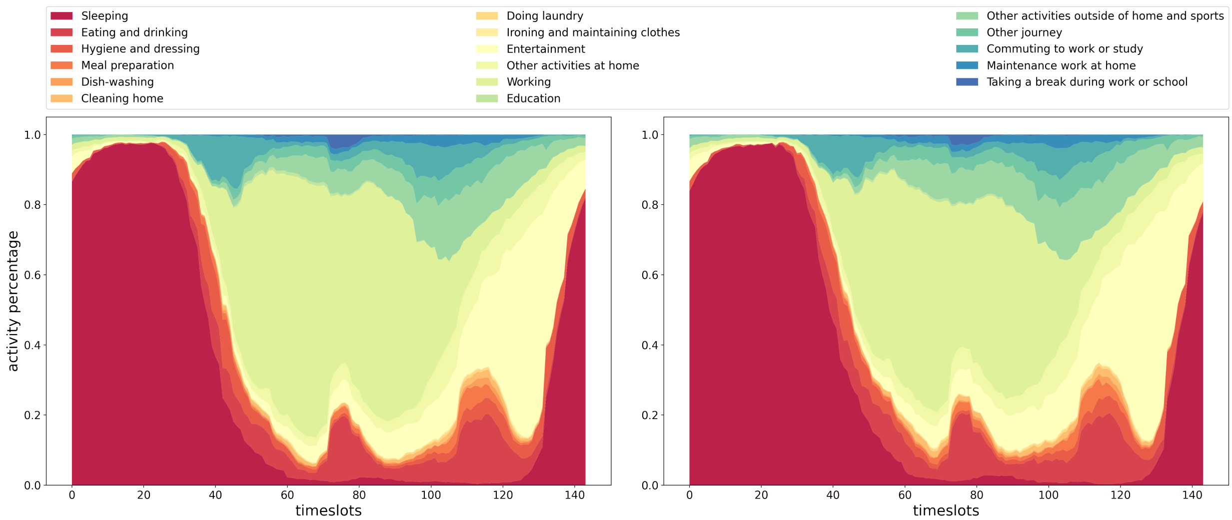

Figure 3: Activity pattern of a fully-employed adult on weekdays: comparing TUS data (left) and model results (right)

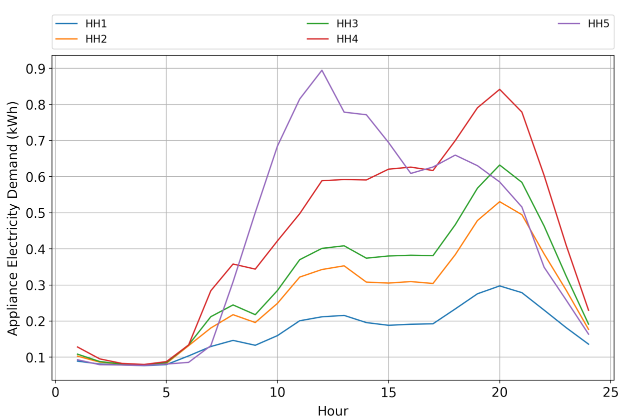

Figure 4: Appliance electricity demand profiles of HH 1-5

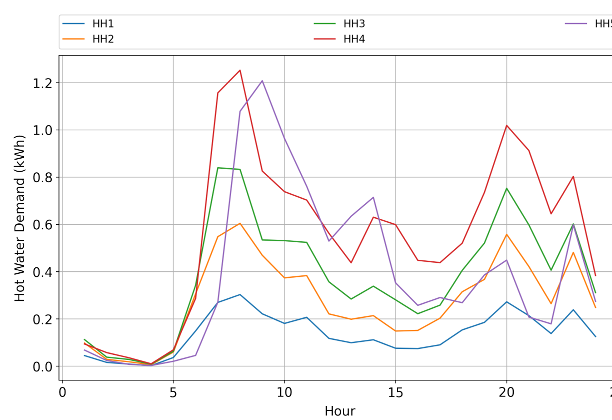

Figure 5: Hot water demand profiles of HH 1-5

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

Table 5
Assumptions for HH3 on building and technology adoption

Component	Assumption
Building	Single-family building (renovated).
Heating Technology	Air-source heat pump.
Cooling Technology	Air-conditioner is adopted (COP = 3).
Space heating tank	Space heating tank is adopted (750L).
Hot water tank	Domestic hot water is adopted (450L).
PV	PV system is adopted (10kW peak).
Battery	Battery is adopted (10kWh).

and 0.42 Euro/kWh and constant PV feed-in price at 0.07 Euro/kWh. The hourly outside temperature is also used as input for the model.

Figure 7 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 "optimization" mode, taking the "simulation" 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

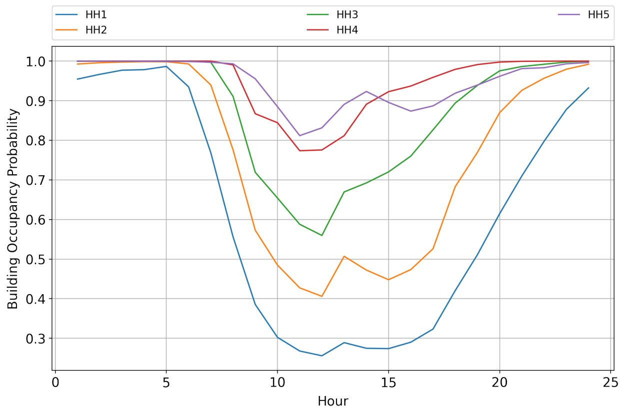

Figure 6: Building occupancy profiles of HH 1-5

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.

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.

4.3. FLEX-Community

By varying the households' behavior profiles and the component assumptions in Table 5, 640 heterogeneous households are constructed. 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 the electricity balance of the community as a whole in summer and winter weeks are shown in Figure 8-9.

As shown, in the summer week, the community can be a net electricity producer in some hours while being a net consumer in other hours. This means the aggregator can make a profit by buying and storing electricity in the first period and then selling it in the second period. Besides, under dynamic electricity price, the aggregator can also 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 P2P trading within the community.

So, taking the households' results from FLEX-Operation as input, the FLEX-Community model is applied to calculate the operation of the energy community: the aggregator optimizes its profit by (1) facilitating P2P electricity trading within the community ($\theta^{bid} = \theta^{ask} = 1$), and (2) optimizing the operation of batteries, including a 10MWh battery owned by itself and the batteries of the households. As a result, the total profit of the aggregator is 424228.6 Euro, including 174786.1 Euro from facilitating P2P trading and 249442.5 Euro from optimizing battery operation. The amount of P2P trading and battery charging/discharging are shown in Figure 10-11.

5. Conclusion

The development of technology and behavior changes brings more complexity to the household sector and necessitates enhanced models to quantify their impacts on the energy demand and facilitate effective policy formulation. Answering this demand, this paper introduces the open-source FLEX modeling suite that covers households' behavior, energy system operation, and interactions in an energy community within a unified framework. It starts from modeling individual members in specified households and provides flexibility for configuring the households' building and technology adoptions. As shown in Section 3-4, FLEX can support analyzing the counterfactual impact of technology and behavioral changes at different levels. Furthermore, the building results can be aggregated to the national level and support analyzing the power system.

One limitation of the study is the detailed validation of households' energy demand profiles, which requires smart meter data with necessary socio-demographic information on the households' composition, employment status, and teleworking behaviors. Updated time-use survey data will also help capture the latest behavior changes in households.

CRediT authorship contribution statement

Songmin Yu: Conceptualization, Methodology (FLEX-Behavior/Operation/Community), Writing first draft, Review and editing. **Philipp Mascherbauer:** Conceptualization, Methodology (FLEX-Operation), Data development, Review and editing. **Thomas Haupt:** Methodology (FLEX-Operation), Data development. **Kevan Skorna:** Methodology (FLEX-Behavior), Data development. **Hannah Rickmann:** Methodology (FLEX-Behavior), Visualization. **Maksymilian Kochański:** Data development, Visualization. **Lukas Kranzl:** Conceptualization, Grant application, Supervision, Project administration.

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.

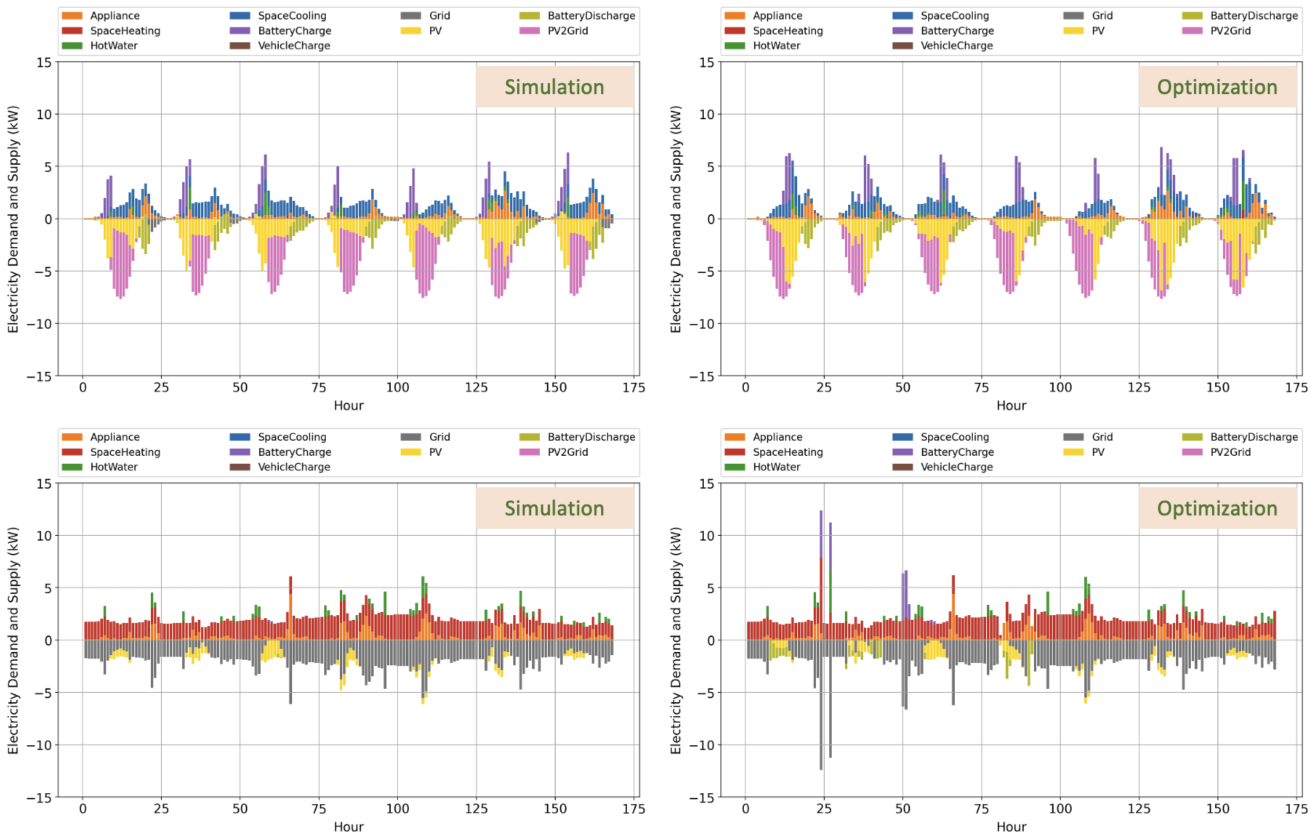

Figure 7: Electricity balance of HH3 in summer (top) and winter (bottom) weeks

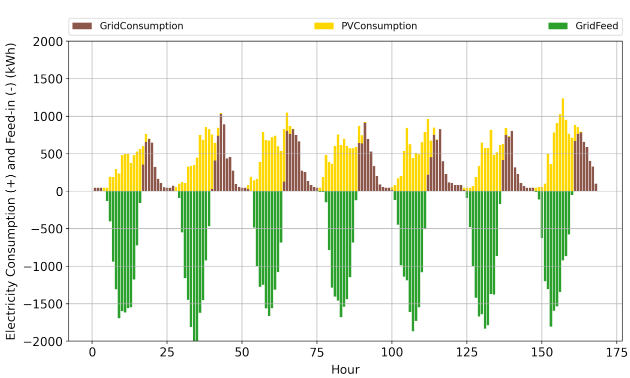

Figure 8: Community electricity balance in a summer week

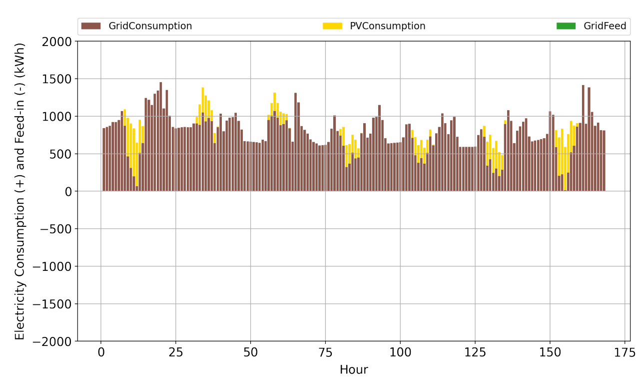

Figure 9: Community electricity balance in a winter week

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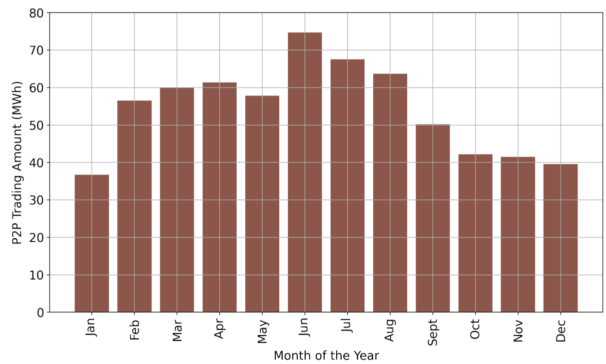

Figure 10: P2P electricity trading amount in the community

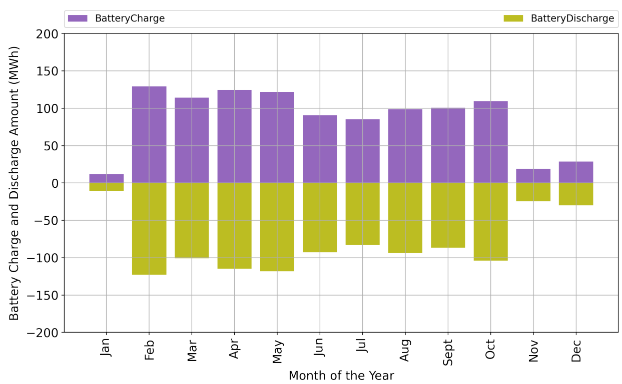

Figure 11: Battery charge and discharge of the aggregator

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