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

Songmin Yu [a,*], Philipp Mascherbauer [b], Thomas Haupt [a,c,d], Kevan Skorna [a,e], Hannah Rickmann [a,f], Maksymilian Kochanski [g], Lukas Kranzl [b]

[a] Fraunhofer Institute for Systems and Innovation Research, Breslauer Str. 48, 76139, Karlsruhe, Germany
[b] Technische Universität Wien, Energy Economics Group, Gusshausstrasse 25-29/370-3, 1040, Wien, Austria
[c] Hochschule Ansbach, An der Hochschule 1, 91555, Feuchtwangen, Germany
[d] Center for Combined Smart Energy Systems, Technical University of Munich, Lichtenbergstr. 4a, 85748, Garching, Germany
[e] BDEW German Association of Energy and Water Industries, Reinhardstrasse 32, 10117, Berlin, Germany
[f] The Interdisciplinary Center for Scientific Computing (IWR), Ruprecht-Karls-University Heidelberg, INF 205, 69120, Heidelberg, Germany
[g] Research and Innovation Centre Pro-Akademia, 9/11 Innowacyjna street, 95-050, Konstantynow Lodzki, Poland

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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 framework 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 Markov core. Second is FLEX-Operation, which models hourly operation of household energy systems across three modes: simulation, perfect-forecasting optimization, and rolling-horizon optimization. Its results are validated with detailed physics-based building simulation software. Third is FLEX-Community, which models the peer-to-peer electricity trading among community members and battery operation of the aggregator. Finally, demonstration results are provided to show the capabilities of FLEX in potential applications for supporting policy design. In summary, FLEX advances existing approaches by bridging detailed household-level behavior and energy system modeling with community-scale optimization, addressing the trade-off between computational tractability and household-level accuracy in the modeling of aggregator-operated energy communities. However, limitations also lie in the requirement of high-quality micro-level data for robust estimation and validation. Future research could investigate system-level dynamics between energy communities and power systems, including participation in ancillary services markets and the evolving regulatory frameworks governing community operations.

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) electric battery storage, either installed at home or integrated into electric vehicles (EVs), and (2) thermal storage, including the building's 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 energy 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 communities" where end-users trade electricity among themselves or through an aggregator, adds new dimensions to energy management.

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* Corresponding author.
E-mail address: songmin.yu@isi.fraunhofer.de (S. Yu).

[1] richardsonpy: https://github.com/RWTH-EBC/richardsonpy.

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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]. Specifically, 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, based on the time-use survey (TUS) data in Sweden, Ref. [4] developed a model for the behaviors of individual occupants following the Markov chain approach, i.e., occupants switching from one activity to another according to the probabilities in a Markov matrix. In addition, the electricity demand profiles are derived from the activity patterns. In Ref. [5], an open-source high-resolution model was developed for UK following a similar approach, which has recently been implemented in Python by a team in Forschungszentrum Jülich.[1] synPRO [6] is another example for Germany, which generates the energy demand profiles for households, covering the electric devices, domestic hot water, and space heating. Ref. [7] improved the approach by (1) considering activities' time-dependent "duration" probabilities, and (2) covering the profiles of driving. Ref. [8] presented a comprehensive review of the available TUS datasets, modeling methods, and implementations in building energy research. Finally, for the remote areas where no TUS data is available, RAMP [9] is an open-source software for the stochastic simulation of user-driven energy demand time series. However, the synthetic profiles are generated based on pre-defined appliances and their operation strategy instead of TUS data and activity modeling.

Second is *household energy system modeling*, which focuses on the operation of a household's energy system and the final energy consumption. One key part of these types of models is to calculate the heating and cooling demand of the building, by two physics-based modeling approaches:

- First are sophisticated software applications which calculate the space heating and cooling demand of individual buildings in detail, e.g., TRNSYS,[2] EnergyPlus,[3] IDA ICE,[4] 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 [10], which makes it possible to integrate them into an optimization algorithm. By comparing the 5R1C approach (DIN ISO 13790[5]) with TRNSYS and EnergyPlus, Refs. [11,12] showed that the 5R1C approach can balance the details of building modeling and the computation demand of optimization.

Using the RC approach, Ref. [13] combined heating and cooling demand with other end-uses (incl. hot water, electric appliances, and electric vehicles) and focused on optimizing the hourly operation of building technologies to minimize the total energy cost in a year. The building technologies also include PV and electric battery. Apart from Ref. [13], there are also studies focusing on different optimization objectives, for example, maximizing the self-consumption rate of a PV system [14] or minimizing the peak demand [15]. Based on these models, the following questions can be analyzed: (1) the operation strategy of the energy storage; (2) the optimal sizes of PV and battery for a building; (3) the potential of load shifting; and (4) the impact of variable electricity prices on household energy system operation with SEMS. Ref. [16] 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 [17] 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. For modeling the energy community, Ref. [23] simulates the impact of the design options of the energy communities on their overall economic and environmental performance. Different demand patterns and technological characteristics are assigned to the participants, and it was revealed that the results depend greatly on the types of participants and their technology configurations. On the other hand, Ref. [24] optimizes the strategy of an aggregator to minimize imbalances in the energy community, in which the members' demand profiles are simplified and classified as non-flexible, semi-flexible, and flexible. This dichotomy reflects a fundamental methodological challenge: detailed representation of individual households' demand patterns and technology characteristics often proves computationally intractable for aggregator-level optimization, necessitating simplifications that may compromise household-level accuracy. Refs. [25,26] provide a comprehensive review of the work on the modeling of energy communities, reflecting the key-determinants of energy communities from a research point of view.

Drawing upon these studies modeling household behavior, household energy system, and energy communities, this paper aims to advance the field through two main contributions. First, we develop an integrated open-source Python framework called FLEX, which consists of three interconnected models: FLEX-Behavior, FLEX-Operation, and FLEX-Community. Building upon methodologies from Refs. [7, 13], FLEX-Behavior generates detailed household behavior profiles that serve as input for FLEX-Operation, which can either simulate household energy system operation or optimize it to minimize annual costs using perfect-forecasting or rolling-horizon approaches. These outputs are then fed into FLEX-Community, which models household interactions within energy communities. This cascading design ensures that detailed assumptions are consistently maintained throughout the modeling chain. Second, FLEX-Community offers a complementary approach to existing energy-community models by leveraging its integration with FLEX-Behavior and FLEX-Operation. This integration allows detailed household characteristics and technology configurations, defined at the behavior and operation modeling stages, to be carried through to the community level analysis. In doing so, we try to address the methodological challenge of maintaining household-level details and heterogeneity in the optimization modeling of aggregator-operated energy communities.

The rest of this paper is organized as follows. Section 2 introduces the three models in FLEX in detail, followed by the demonstration results in Section 3. In Section 4, we discuss the strengths and limitations of FLEX. Finally, we conclude in Section 5, including its existing and potential applications in supporting policy design.

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

[3] https://energyplus.net

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

[5] 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.

2. Model

In this section, we introduce the three components in the FLEX framework, which capture the household behavior, energy system operation, and interactions in an energy community in hourly resolution.

- First is *FLEX-Behavior* (Section 2.1), which models the energy-related behavior of a specified household. For each individual household member, the activity profile is modeled at a 10 min 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* (Section 2.2), 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 electric 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* (Section 2.3), 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 of community members to buy at lower prices and sell at higher ones.

2.1. FLEX-Behavior

FLEX-Behavior models the energy demand and building occupancy profiles of a specified household in hourly resolution. To achieve this, the model begins by modeling the activity profiles of individual household members, based on the time-use survey[6] data from Germany.

The diaries from the survey respondents consist of 165 coded distinct activities in 10 min 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

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 min 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 midnight 0:00, a starting activity is selected according to the TUS data to initialize the simulation. For example, for a fully-employed adult, we calculated the probabilities of all possible activities at 0:00 on a weekday, and the probability of "sleeping" is 86.52%.
- Second, for this selected initial activity, its duration is drawn from an estimated distribution. Following Ref. [7], the frequency of all possible durations of each activity in the dataset are counted, given the combination of (1) person type, (2) day type, and (3) time. Then, the counted frequency is further used to develop the duration distribution of each activity, i.e., the duration distribution of each activity depends on its starting time. This is important to reflect that, for example, the activity "sleeping" lasts longer if it starts at 0:00 than around noon.
- Third, by the end of the initial activity, the next activity is selected according to a Markov matrix as described by Eq. (1). 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 ($t \geq 2$). As shown in Table 1, there are 17 states (activities) in total, i.e., $n = 17$. Besides, we chose the first-order Markov chain here as suggested by similar studies [4–7]. In this way, we prioritize the estimation of time-dependency of switching probabilities given the limited amount of empirical data.

$$P = \begin{bmatrix} p_{11}(t) & p_{12}(t) & \cdots & p_{1n}(t) \\ p_{21}(t) & p_{22}(t) & \cdots & p_{2n}(t) \\ \vdots & \vdots & \ddots & \vdots \\ p_{n1}(t) & p_{n2}(t) & \cdots & p_{nn}(t) \end{bmatrix} \quad (1)$$

where $\sum_{j=1}^{n} p_{i,j} = 1$, for any $1 \leq i \leq n$

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

By repeating Steps 3–4, 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. Fig. 1 shows an example of the activity pattern of a fully-employed adult on weekdays, comparing the TUS data (left) and model results (right). To quantitatively measure the difference between TUS data and model results, for each of the 144 time slots in Fig. 1, we calculated the Jensen–Shannon Divergence (JSD) between the two "activity percentage vectors", resulting a range [0.033, 0.174] with the mean value equal to 0.087.

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 with predefined trigger probabilities (see Table 1). The appliances are selected to cover the most common household devices and their probabilities are developed based on the ownership rate,[7] then calibrated so that (1) the electricity demand profiles are reasonably close to the profiles from empirical studies [27] with peaks in the evening and around noon, and (2) the annual electricity demand is close to the Destatis data [28] (see

[6] 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).

[7] Source: www.statista.com.

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 a 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).

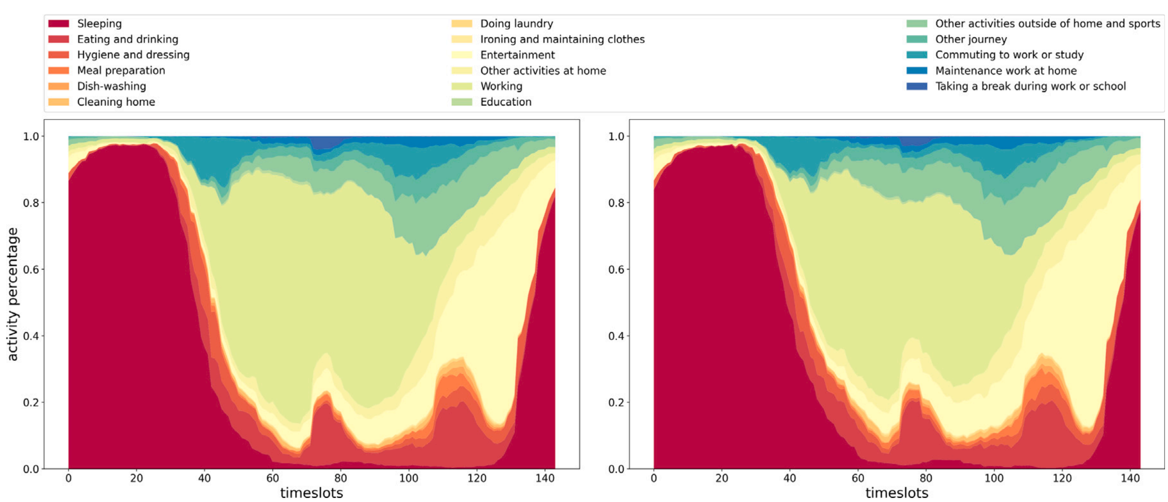


Fig. 1. Activity pattern of a fully-employed adult on weekdays: German TUS data (left) and model results (right).

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 a 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 Fig. 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.

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 Fig. 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 Fig. 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^t_s is calculated with Equation (b), in which θ^t_{ma} represents the average temperature of the building mass in the previous (θ^{t-1}_m) and current (θ^t_m) hour, as calculated by the Equation (c). Specifically, θ^t_m is calculated by Equation (d), with $\phi^t_{m\_tot}$ denoting the net heat

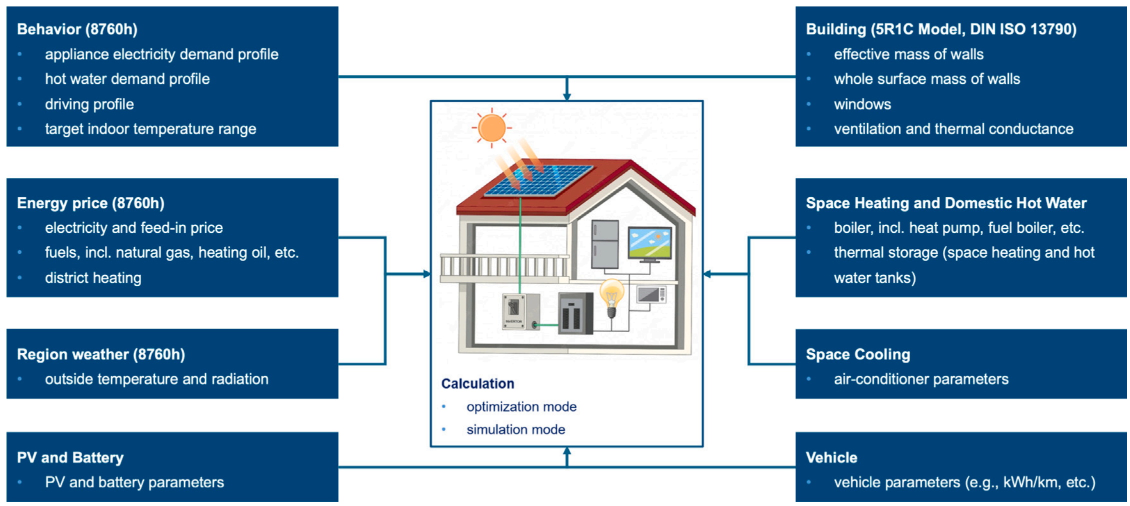
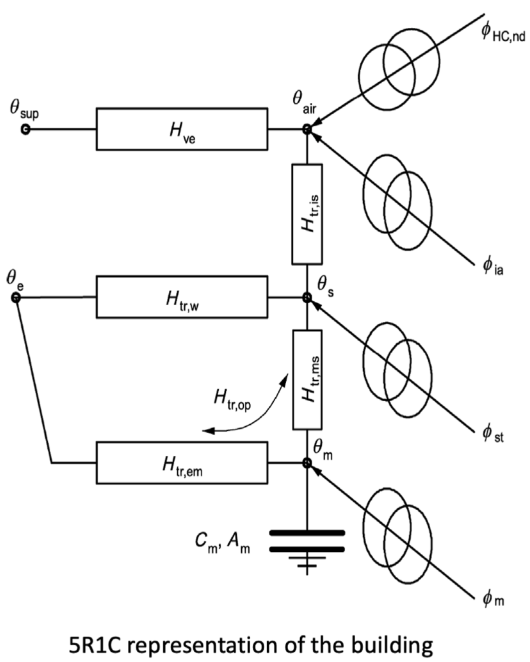


Fig. 2. Structure of the FLEX-Operation model.



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

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

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

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

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

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

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

Fig. 3. Circuit model for the building and key equations from DIN ISO 13790.

gain (i.e., internal and solar gains minus loss), calculated in Equations (e)–(g). ϕ^t_{sol} means the solar gain.

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.[8] The comparison results are shown in Fig. 4, with the difference in percentage marked. As shown, the FLEX-Operation model approximates the annual heating demand for each building relatively well, which is in accordance with results from Refs. [29,30]. 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 Eq. (2).

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

[8] 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/K m^2	building specific
C_m	the total thermal capacity of the building mass	J/K	$C_m = \sum_j (k_j \times A_j)$
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	$H_{tr,em} = 1/(1/H_{op} + 1/H_{tr,ms})$

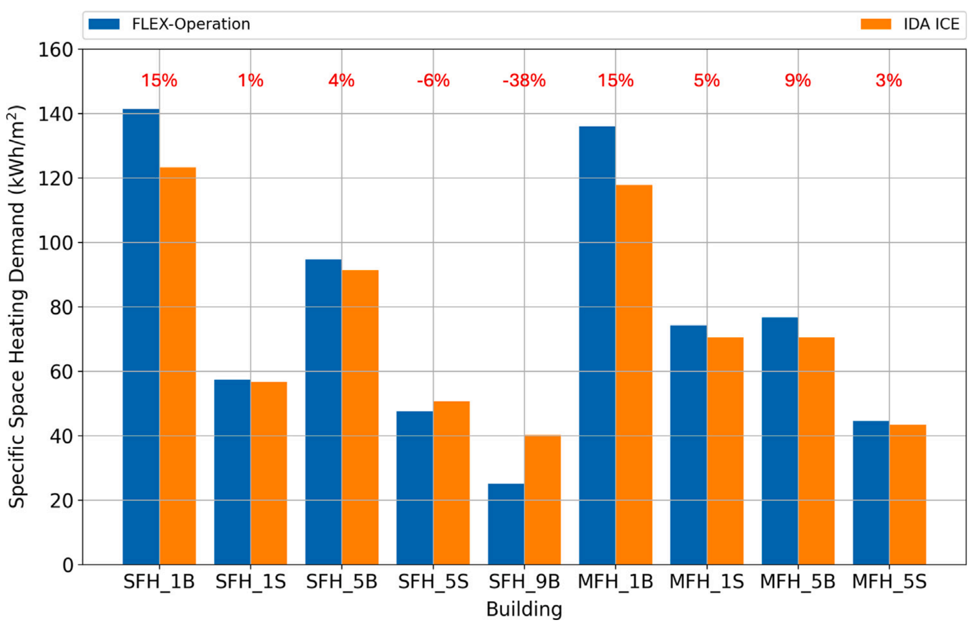


Fig. 4. Building heating demand comparison between FLEX-Operation and IDA ICE.

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 [31–34]. The size of the heat pump is decided according to the maximum 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 0.2 W/m^{2}K. The minimum temperature of the tanks equal to 28 °C, based on which a tank's state-of-charge (SOC) is calculated by Eq. (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 Eq. (4), with A_{tank} denoting the surface area of the tank. The typical sizes of space heating and domestic hot water tanks are 700L ($A_{tank} = 4.62$ m^2) and 300L ($A_{tank} = 2.63$ m^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[9] 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

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

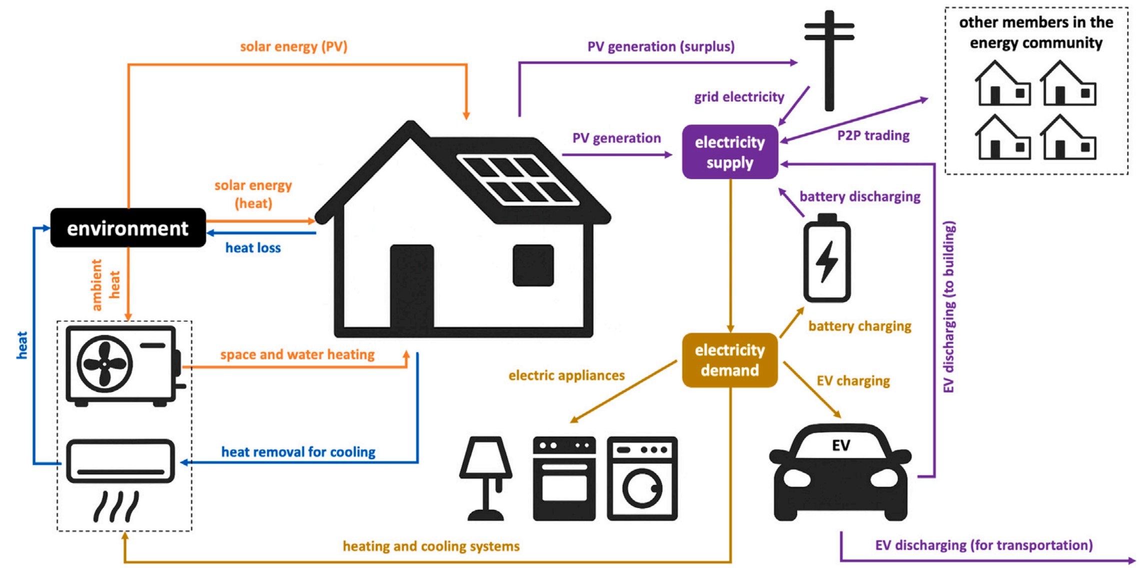


Fig. 5. System boundary and energy flows in FLEX-Operation.

level by taking the weighted average. The weights are regional floor areas provided by the HOTMAPS project.[10] For the battery, we assume the charging and discharging efficiency are both 95% with maximum power 4.5 kW. The SOC of battery is modeled either following a rule-based approach or optimized, according to the running mode of the model (see Section 2.2.5).

2.2.4. Vehicle modeling

As shown in Fig. 2, FLEX-Operation also considers an optional vehicle for the household. If included, the driving profile of the vehicle is used as input. Following Ref. [35], driving profiles are developed based on the MOP[11] data for FLEX. A typical driving profile 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

In summary, Fig. 5 shows the system boundary and energy flows of FLEX-Operation. 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.[12]

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 Eq. (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 (Eq. (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 (Eq. (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 Fig. 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 Fig. 6 (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, Fig. 6 (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.

10 www.hotmaps-project.eu

11 https://mobilitaetspanel.ifv.kit.edu/english/

12 Depending on the complexity of the building configurations and the strength of the computer, our runs show that the reference mode takes no longer than 1 s, but the two optimization modes can take 12–40 s.

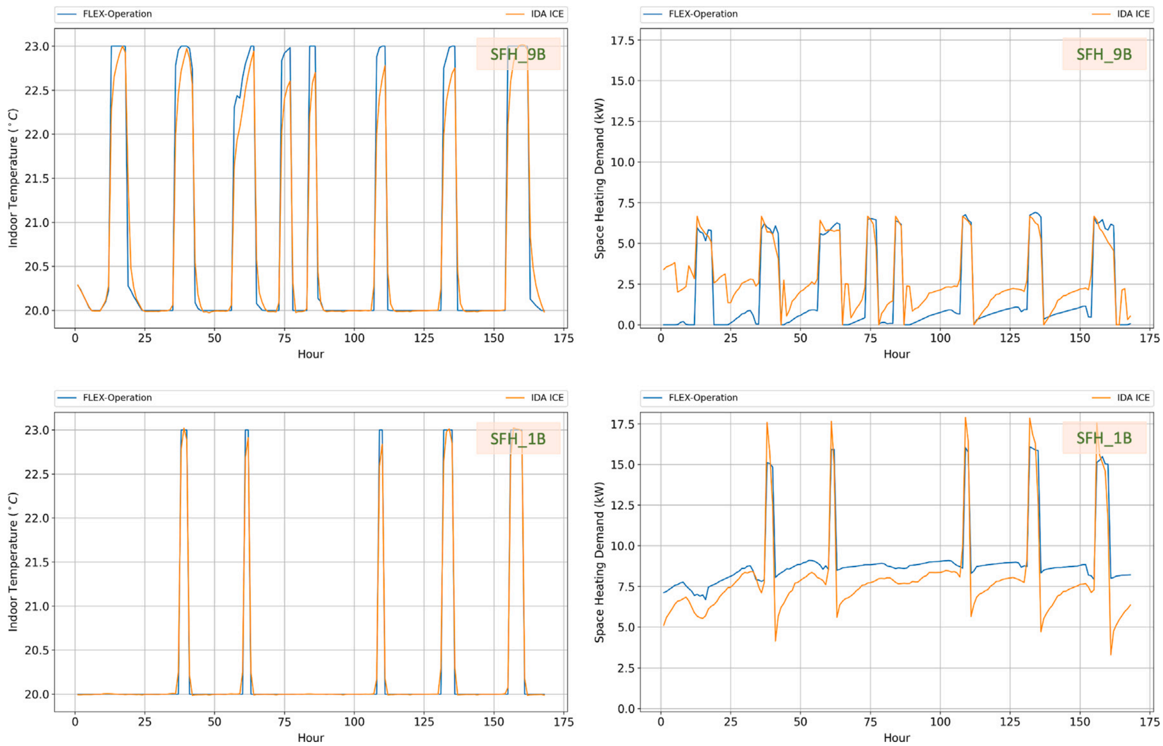


Fig. 6. Comparison between FLEX-Operation and IDA ICE: indoor temperature (left) and heating demand (right).

To quantitatively measure the difference between the hourly results IDA ICE and FLEX-Operation, the Jensen–Shannon Divergence (JSD) are calculated again for the four timeseries shown in Fig. 6: first, for SFH_9B, the JSD for indoor temperature and heating demand are 0.004 and 0.291; second, for SFH_1B, the JSD for indoor temperature and heating demand are 0.001 and 0.047.

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 as the perfect-forecasting optimization mode. As shown in Fig. 7, the time window for Day N starts at 12:00 and the optimization horizon is 36 h, based on the forecasts of electricity price, environment temperature, and radiation. Then, only the results in the first 24 h are kept and the optimization starts again at 12:00 on Day $N + 1$.

We designed it in this way because the electricity price forecasts are updated at 12:00 every day and weather forecasts within 36 h 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 h 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" [36] or "terminal cost" [37] of a storage. As far as we are aware, 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 h as an estimate. Fig. 7 shows the dual variables of the terminal value in rolling-horizon optimization and the average shadow price in perfect-forecasting optimization.

Finally, Fig. 8 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 the first two models, FLEX-Community provides a complementary approach to existing literature, which maintains household-level details and heterogeneity in the optimization modeling of aggregator-operated energy communities. Taking the perspective of an aggregator of the community, FLEX-Community 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 (FIT_t), while some other households buy electricity from the grid at a higher price (P_t). In such hours, we assume the aggregator can facilitate P2P trading by buying electricity from the households with surplus generation and selling it to the other households. Specifically, we assume the aggregator buys electricity at price $P_t^{bid} = \theta^{bid} FIT_t$, which is no lower than the feed-in tariff ($\theta^{bid} \geq 1$), so these households are incentivized to sell the surplus to the aggregator instead of the grid. Then, we assume that the aggregator will at the same time sell the surplus to the other households at price $P_t^{ask} = \theta^{ask} P_t$, which is cheaper than buying from the grid ($\theta^{ask} \leq 1$). As a result, the aggregator can make a profit in the hours when P_t^{ask}

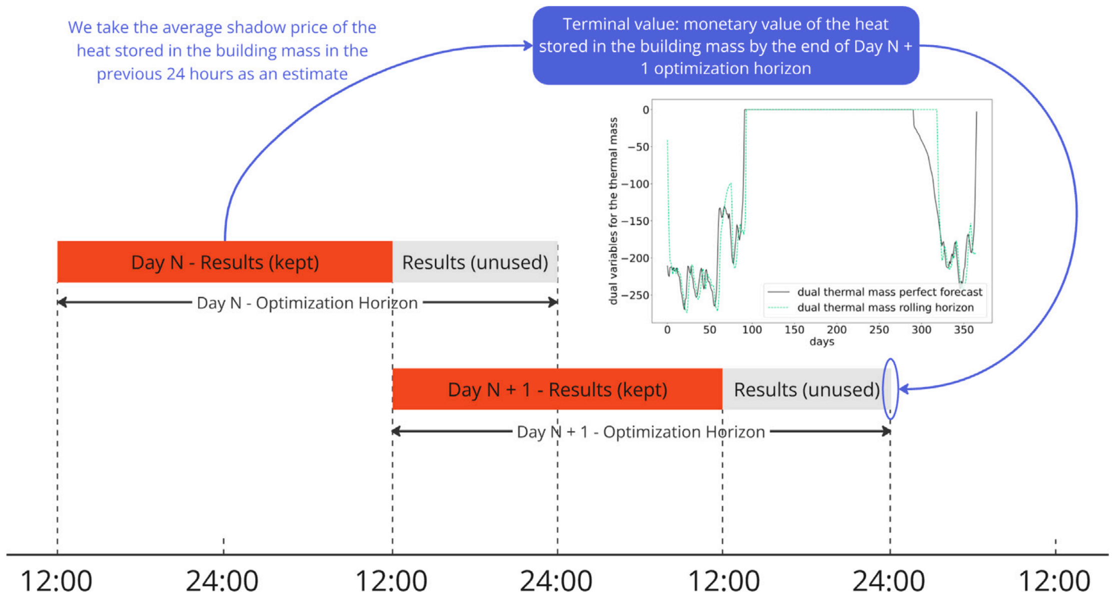


Fig. 7. Optimization timeframe of the rolling-horizon optimization mode in FLEX-Operation.

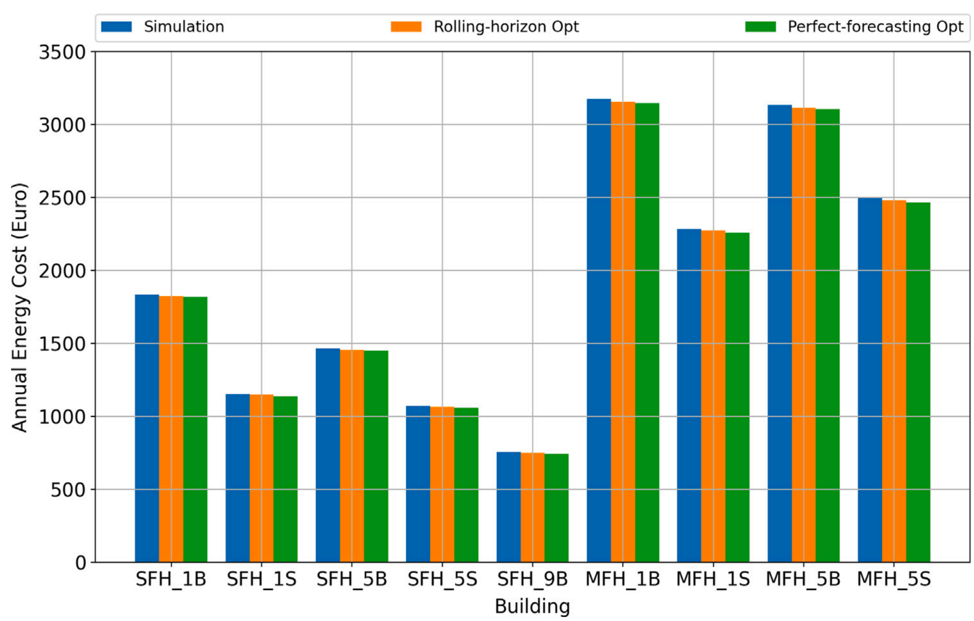


Fig. 8. Annual energy cost comparison between the three running modes.

is higher than P_t^{bid}, the profit π^{p2p} is calculated by Eq. (8). In FLEX-Community, the two parameters – θ^{bid} and θ^{ask} – are defined to reflect the strategy of the community aggregator or the regulations that the aggregator faces.

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

Second, in addition to facilitating P2P trading in real-time, the aggregator can also buy electricity at a lower price and sell it when the price is higher. For this, the aggregator can invest in a centralized electric battery or use the batteries of the households. Taking the results of heterogeneous households calculated in the FLEX-Operation, the FLEX-Community model receives the remaining capacity of each household in each hour. These resources are pooled in the community and their operation is optimized by the aggregator for profit (π^{opt}). The larger the total (centralized + decentralized) battery capacity, the higher π^{opt} the aggregator can earn. In return, this profit is split between the aggregator and the households according to the energy-political framework agreed by both sides.

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 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 Fig. 9. The annual results are summarized in Table 4.

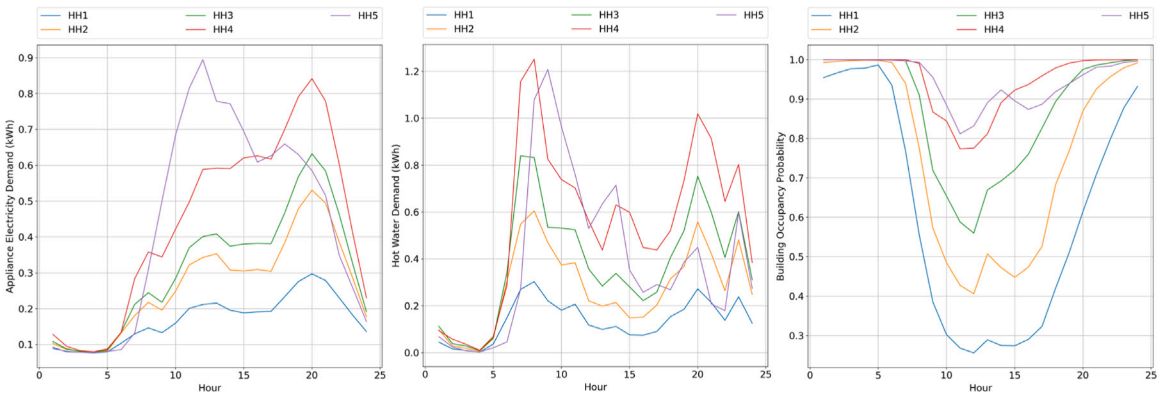


Fig. 9. Average appliance electricity demand, hot water demand, and building occupancy profiles of HH 1–5.

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

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

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, 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 moderately 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 regardless of whether 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.

Fig. 10 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,[13] 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 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-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.

Fig. 11 shows the electricity balance of the community as a whole in summer and winter weeks. So, half of the households with 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, Fig. 12 shows the strategy optimized for the aggregator: P2P electricity trading amount and battery charge/discharge in each month of the year.

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. Finally, by taking results from the first two models, FLEX-Community

[13] 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 do not focus on a detailed comparison of the two here.

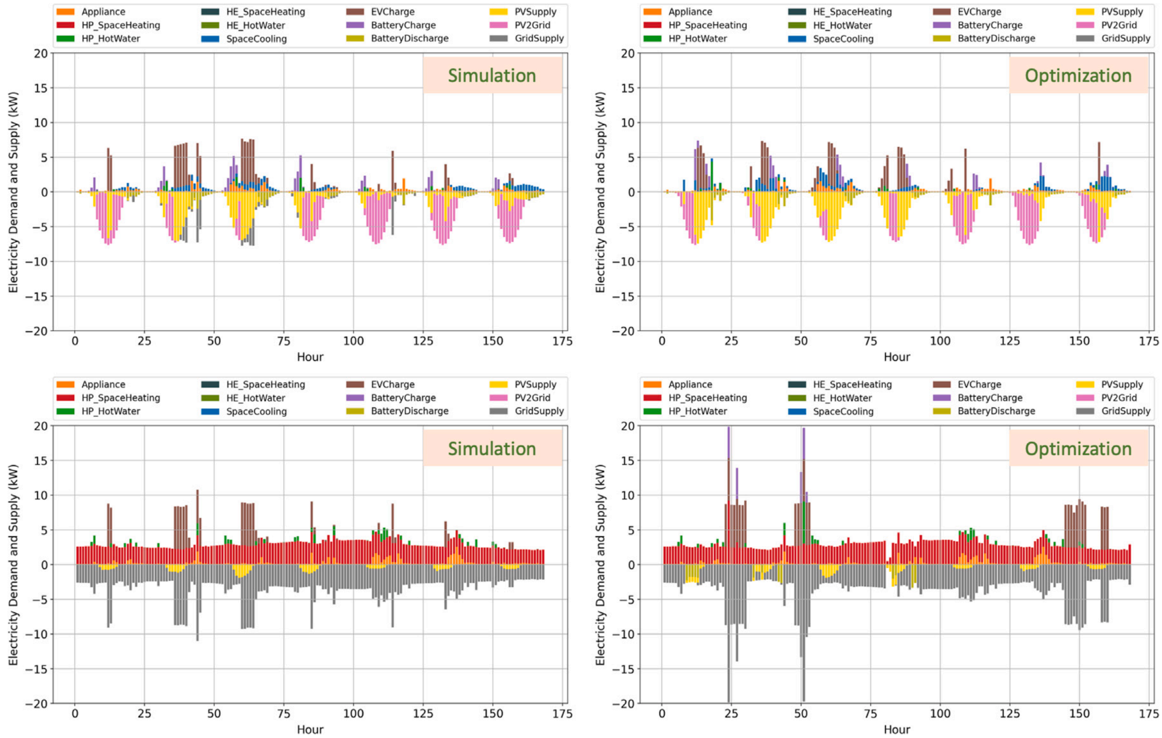


Fig. 10. Electricity balance of HH3 in summer (top) and winter (bottom) weeks.

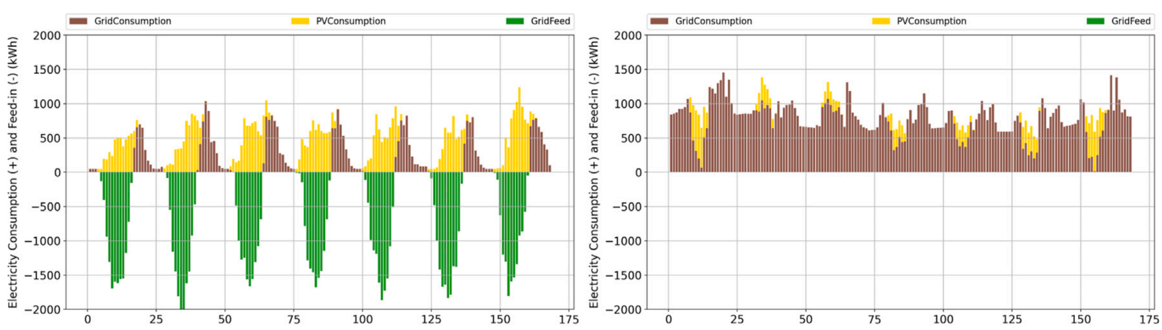


Fig. 11. Electricity balance of the energy community (50% PV adoption) in summer (left) and winter (right) weeks.

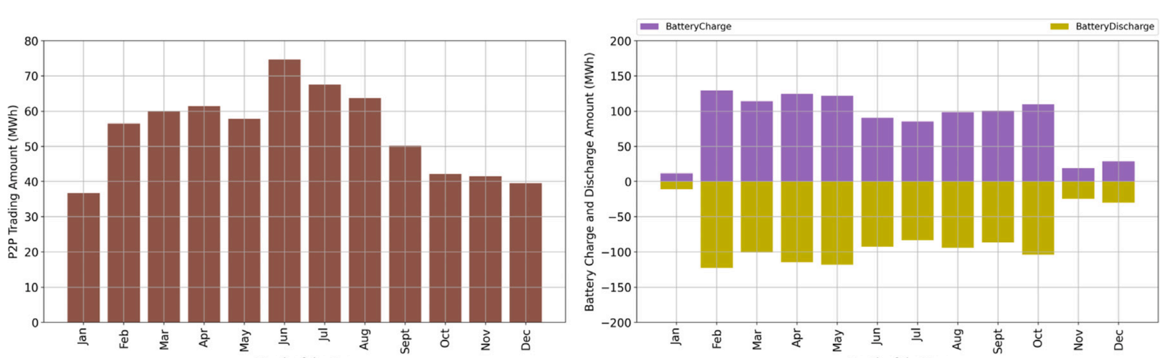


Fig. 12. P2P electricity trading amount and battery charge/discharge in the community.

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

- First, the current version of FLEX-Behavior is based on data from the Germany time-use survey collected in 2012–2013, limiting its applicability to other countries. The households behavior and energy usage patterns could also have changed especially due to the impact of COVID-19 (e.g., teleworking). The model requires updates when the micro-level data from the latest time-use survey become available. In addition, the profiles of electricity and hot water demand, as well as building occupancy, should be validated again with more detailed empirical data, preferably from the typical households categorized by socio-demographic properties. The seasonal variations in the behavior patterns of households (e.g., different routines in summer and winter) should also be included. Finally, the modeling of appliances use can be improved, with trigger probabilities estimated from micro-level data and more detailed usage behavior (e.g., minimum off time) considered.
- 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. [7], 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. [35], we use driving profiles developed from MOP data, which has a longer observation period, offering better insights into daily driving patterns compared to MiD[14] data used in Ref. [7].
- 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. Furthermore, the heat distribution system in FLEX-Operation can be improved to better represent the floor heating system, which can not only lower the supply temperature and increase the efficiency of heat pumps, but also increase the heat capacity of the building and impact the optimization result.
- Fourth, regarding the energy-political framework of energy communities, FLEX-Community is designed from the perspective of an aggregator who optimizes its strategies for facilitating peer-to-peer trading and operating batteries. Two parameters (θ^{bid} and θ^{ask}) are used to represent the aggregator's pricing strategy, which also decides the profit allocation between community members. 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. In addition, the energy-political framework of energy communities is an important and dynamic aspect, and the model could be enhanced to represent a broader range of regulatory scenarios and community structures.

Overall, compared with existing studies, the main strength of FLEX is its ability to bridge the gap between detailed household-level behavior and energy system modeling and community-scale optimization through its integrated, cascading framework. In particular, it offers a complementary approach to resolve the traditional trade-off between computational tractability and household-level accuracy in the modeling of aggregator-operated energy communities. On the other hand, the primary limitations of FLEX also lie in its detailed modeling of household behavior and technology systems, which demands high-quality micro-level data for estimation and validation. In addition, an important extension for FLEX as well as the broader field is to investigate the system-level dynamics, specifically the interface between energy communities and power system operations. Critical areas for investigation include the optimization of value streams through participation in ancillary services markets and demand response programs. Moreover, the evolving regulatory framework governing energy communities – encompassing aggregator roles, profit allocation mechanisms, and market participation rules – constitutes a crucial domain for further investigation, particularly given the dynamic nature of energy policy landscapes.

5. Conclusions

Technological advances and changing behaviors are fundamentally reshaping household energy consumption patterns, necessitating sophisticated models to quantify their impacts and inform effective policy making. This paper presents FLEX, an integrated open-source Python framework for modeling household behavior, energy system operation, and community-level interactions. Through its three interconnected components – FLEX-Behavior, FLEX-Operation, and FLEX-Community – the framework enables comprehensive analysis from individual household consumption to community-scale dynamics. With comprehensive validation and cases calculation, the framework's capabilities are demonstrated. The strengths and limitations of the framework are also discussed.

Benefiting from its granular household-level modeling and integrated framework, FLEX provides a robust analytical foundation for evaluating energy policies and regulatory frameworks. The framework has already demonstrated its versatility across multiple applications: assessing smart charging impacts on electric vehicle ownership costs [35], evaluating prosumaging effects on grid expansion costs in combination with a distribution grid planning model [38], and analyzing system-level implications of smart energy management [17], variable electricity pricing [39], and decentralized heat pumps as flexibility options [40]. Looking forward, FLEX can further contribute to understanding how energy communities interface with the broader power system, particularly regarding participation in ancillary services markets and demand response programs.

CRediT authorship contribution statement

Songmin Yu: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Philipp Mascherbauer:** Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Thomas Haupt:** Writing – review & editing, Software, Methodology. **Kevan Skorna:** Writing – review & editing, Methodology, Data curation. **Hannah Rickmann:** Writing – review & editing, Visualization, Software, Data curation. **Maksymilian Kochanski:** Visualization, Validation, Methodology, Data curation. **Lukas Kranzl:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Conceptualization.

14 https://www.infas.de/studien/mobilitaet-in-deutschland-mid/

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Songmin Yu reports financial support was provided by European Commission. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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