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Notes

Abstract

This paper addresses the following question: How can smart energy management system (SEMS) influence the residential electricity consumption at both individual household and national level? First, we developed an hourly optimization model for individual households. The energy cost of an individual household is minimized under given assumptions on outside temperature, radiation, (dynamic) electricity price, and feed-in tariff. By comparing the optimization to the reference scenario, we show the impact of SEMS on grid-electricity consumption and photovoltaic (PV) self-consumption at the individual household level. Second, to aggregate the results to the national level, we constructed a detailed building stock taking Austria as an example. By aggregating the results of 2112 representative households, we investigate the impact of SEMS in the residential building stock on the national electricity system. As a result, we found that for individual single-family-houses (SFHs) with PV (no battery) and heat pump adoption, SEMS can significantly reduce the grid-electricity consumption up to 40.7% for a well-insulated building. At the national level we found that, for the buildings with 5 kWp PV but without hot water tank or battery storage, SEMS can still reduce the grid-electricity consumption by 7.4% by using the building mass as thermal storage.

Keywords: demand-side management, PV, heat pump, energy storage, optimization, building stock

Contents

1 Introduction

Under the scenario with large share of renewable generation, demand-side management (DSM) measures can become increasingly relevant for multiple sectors to balance the electricity supply and demand (Sioshansi 2019). For the residential sector, the example is the diffusion of smart energy management systems (SEMS). Combining heat pump (HP), photovoltaic (PV), battery and thermal storage (hot water tank and building mass), a household can optimize the operation of technologies for lower peak loads, less grid-electricity consumption, as well as lower energy cost. The question we want to answer in this paper is, how SEMS can influence the residential sector's electricity consumption at both individual household and national level.

In the residential sector, the diffusion of DSM measures is promoted by declining costs of PV and batteries, as well as other support policies. In Austria, the revision of the Renewable Energy Expansion Act (Nationalrat 2021) sets the course for renewable energy communities which is in line with the RED II[1]. Self-generated renewable electricity can be sold within Austria to the members of an energy community for a self-determined price with a reduced electricity grid fee. As a result, it is expected that the number of prosumagers[2] in Austria might increase in the coming years. In this regard, this study aims to investigate how SEMS can affect electricity consumption of the residential sector at both individual household and national level.

Numerous studies have analyzed the potential impact of SEMS (or DSM measures) in the residential sector. Kandler (2017) established an optimization model for single family houses (SFH) and showed that hot water storage and PV systems can significantly support the SEMS. Yousefi (2020) and Salpakari et al. (2017) analyzed the impact of DSM measures on the individual cost savings. These models cover the energy consumption of a household from different aspects (incl. appliances, space heating, hot water) and consider the flexibility based on battery storage, smart devices, electric vehicles, thermal mass of the building, etc. However, there are still two major limitations. First, space cooling is often missing in modeling household energy consumption (Kandler 2017; Angenendt et al. 2019). Second, these studies focus only on individual household level and lack SEMS implications at the national level. Sperber et al. (2020) investigated the demand-response potential for SFH with HPs in Germany and found that the maximum electric shiftable load through HPs in German SFH is 57 GW_{el}. Weiß et al. (2019) established a link to a national building stock of Austria and also focused on shifting peak demands on single days. Both these approaches aim to investigate the demand shift potential at a given time, but not the implications on the electricity demand over the whole year.

So, to fill in the research gaps and answer our research question, this study contributes in the two aspects as follows:

- First, we established an hourly optimization model that covers the demand of households from appliances, space heating, space cooling, and hot water. Besides, it also considers the outside temperature and radiation profiles, building parameters, and technologies including PV, battery storage, hot water tank, and building mass as thermal storage. Both heating and cooling

[1] Renewable Energy – Recast to 2030 (RED II) [3].

[2] "Prosumagers" refers to the households who can produce based on PV while consume, and at the same time, can also manage (optimize) the operation of technologies (especially energy storage) for lower energy cost [1].

demand are calculated with a 5R1C approach. The model can also be run without optimization, i.e. the “reference mode”, compared with which the impact of SEMS is shown.

- Second, to capture the implication of SEMS at the national level, we established a link to a detailed building stock model (INVERT/EE-Lab) (Müller 2021), and Austria is taken as an example. We considered the different building archetypes of SFH and the different behavior of households. In total, we have 2112 representative household cases. To the authors’ best knowledge, this is the first study that uses optimization to show the impact of SEMS at a national level for the case of Austria by creating an explicit link to an established building stock model. Furthermore, we examined the effect of two different policy scenarios: flat and variable electricity prices.

The remainder of this paper is structured as follows. Section 2 gives an overview of existing studies on SEMS in residential buildings and focuses on the heating and cooling demand modeling. Section 3 introduces our model in detail, followed by Section 4 which provides the input data and scenario definitions. Then, in Section 5, we present the results by comparing the optimization and reference modes at both individual household and national level. At last, we conclude in Section 6, discuss the limitations of this approach, and point out the need for further research.

2 Literature review

Developing optimization models for household energy consumption has been motivated by different research focuses, for example, self-consumption rate of PV plus battery system (Klingler 2018), optimal size for PV and battery adoption (Kandler 2017), the impact of DSM measures on load shifting of households (Georges et al. 2014), etc. Correspondingly, the studies may cover different energy demands and technologies, and may even have different objective functions.

To evaluate the diffusion of PV plus battery system, Klingler et al. (2018) developed an optimization model to maximize the self-consumption rate of PV generation, based on the flexibility from an electric vehicle and a HP. Exogenous profiles of electricity consumption, EV charging, and heating demand are used to capture the behavior of households. In this way, the study evaluated the market potential of PV plus battery systems in Germany. Angenendt et al. (2019) optimized a SFH to minimize the household's energy cost and to find the optimal system configuration. They included thermal- and battery storage, PV, and the respective investment costs. However, space cooling is not included. On the other hand, Kandler (2017) analyzed the optimal PV panel and battery size based on an optimization model that minimizes households' energy costs. This study further considers the hot water tank and building mass as thermal storage to better capture the demand-side flexibility.

Several studies suggest that the potential of using thermal mass for load shifting is significant, and the interaction between the heating system and the thermal mass is an important factor (Wolisz 2013; Reynders et al. 2013). With a heating period of two hours, the heating demand of the following four hours can be reduced by up to 20%. Georges et al. (2014) simulated a single household in detail and found that 3% to 14% of the load can be shifted by using the building's thermal mass with a well-insulated building. Other studies suggest that electric load can easily be shifted by electrically heating the concrete slab (Olsthoorn et al. 2019). They find this solution feasible for shifting morning and evening peaks in houses ranging from 80 m^2 to 200 m^2 with a slab thickness of 15 cm in the Canadian building stock. Luo et al. (2020) continued this research and optimized the parameters for electric heating in concrete slabs concerning shifting potential, thermal comfort, and costs. They found that insulation thickness had the most significant effect. The limiting factors for utilizing thermal mass are not the thermal mass itself but mainly the insulation and heat distribution system. Le Dreau et al. (2016) modeled two different residential buildings and examined their potential for heat storage and heat conservation. The findings showed that the potential of thermal mass depends on many factors like insulation and heat distribution system and the season of the year. On the other hand, the thermal mass also has a significant impact on the cooling needs. Kuczynski et al. (2020) compared two almost identical buildings except for their external and internal walls in a case study. Compared to the lightweight structure house, the cooling demand with concrete walls was reduced by 75% at a 26 °C set temperature. However, using building mass as thermal storage for load shifting can also lead to higher energy consumption because of greater heat losses. There are two kinds of models to integrate the building mass as energy storage into an energy demand model.

- First, there is sophisticated software (e.g. TRNSYS, EnergyPlus) that calculates the heating and cooling demand of a building in detail. However, the disadvantages are: (1) a significant number of building parameters must be estimated as inputs; (2) the calculation demands high computation power; (3) it is difficult to integrate other aspects (e.g., appliance electricity, PV, electric vehicle, etc.) into an optimization framework.

- Second are simplified models where buildings are represented by resistances and capacities, referred to as "RC models". Due to the simplicity, we can combine heating and cooling with other energy consumption into an optimization framework. Furthermore, we can use sophisticated software for validating the results of RC models. Taking the Irish building stock as an example, Heinen et al. (2017) implemented a resistance-capacity (RC) approach. They concluded that the households with electrified heating systems could reduce their heating costs to the cost of benchmark technology (gas boilers) by utilizing the thermal inertia of their building.

One example of the RC models is the 5R1C model, described in the DIN ISO 13790, where a building is represented by 5 resistances and one capacity. The norm offers two basic procedure methods: (1) quasi-steady-state approach, which calculates the thermal loads of building over a month; (2) simplified hourly approach, which calculates the heating and cooling demand in hourly resolution.

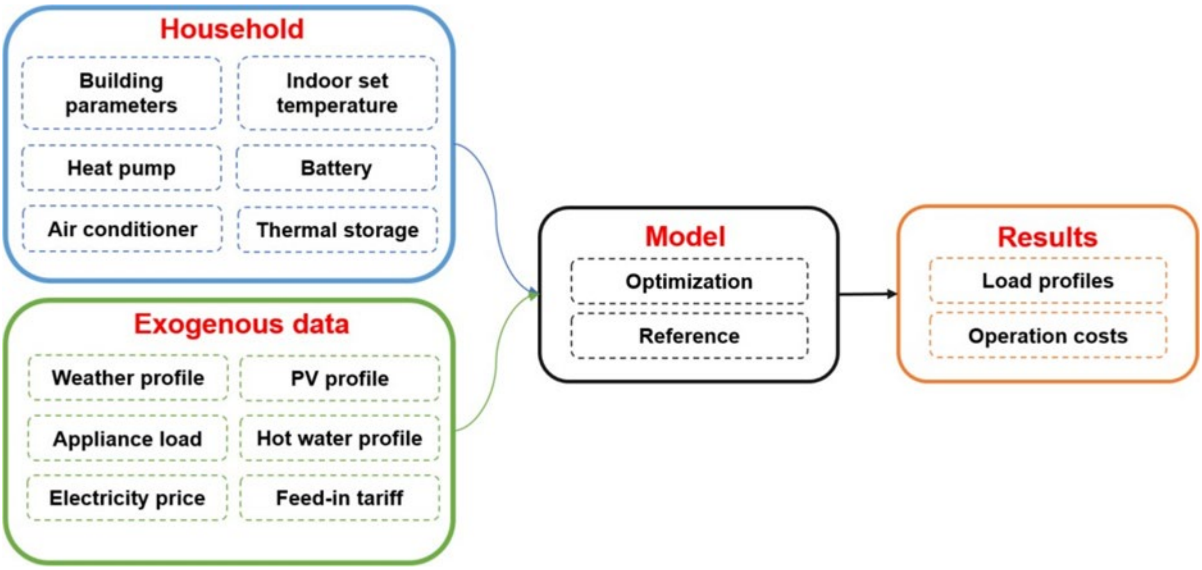
However, Corrado and Fabrizio (2007) found that the quasi-steady approach is unreliable because it takes mean outdoor temperature and a steady indoor temperature as input, then continuously calculates the operation of heating and cooling technologies. On the other hand, Bruno et al. (2016) compared the simplified hourly approach to the results from TRNSYS. The heating demand calculated by the 5R1C model is similar to TRNSYS results for single-family compact buildings but not for large buildings and buildings with low thermal inertia. The cooling load diverges strongly for small buildings but becomes more accurate for larger buildings. Kotzur (2018) states that the 5R1C approach on an hourly basis provides satisfactory results for heating while the cooling need is often overestimated. One reason is the neglect of household behavior: the shading systems are usually closed in summer when the solar irradiance is high. Furthermore, Sperber et al. (2020) compared a group of RC models, namely 1R1C, 2R2C, 3R2C, 4R3C, and 5R3C with the results from TRNSYS. The findings showed that adding a second capacity improved modeling significantly, especially for buildings that use low-temperature floor heating instead of radiators. However, they did not test the 5R1C approach described in DIN ISO 13790. The DIN ISO 13790 was replaced by the ISO 52016 in 2017, where the number of resistances and capacities depends on the building geometry and features.

This study chooses the previous norm (DIN ISO 13790) to model heating and cooling demand. The computational effort for implementing the norm ISO 52016 would be enormous, especially if we want to combine the optimization with other technologies. In the ENTRANZE project, Müller et al. (2014) tested the previous norm (DIN ISO 13790) against the results from Energy Plus and INVERT/EE-lab. As shown in the results, the hourly model overestimates cooling energy needs, especially in Mediterranean climates, but the energy needs for heating are in accordance. The comparison is made on a monthly basis where the energy needs of the hourly calculations are added up.

3 Model

Figure 1 presents the overall structure of our model for individual households. The model takes the specific parameters of a single household into account and calculates the energy demand and operating costs over the whole year on an hourly basis. A single household consists of the building parameters, a thermal and battery storage optionally, a rooftop PV, an HP, either air sourced or ground sourced, and an optional air-conditioner (AC) for cooling. In addition, the indoor set temperature can be varied depending on the household's preferences.

Figure 1: Structure of the Model

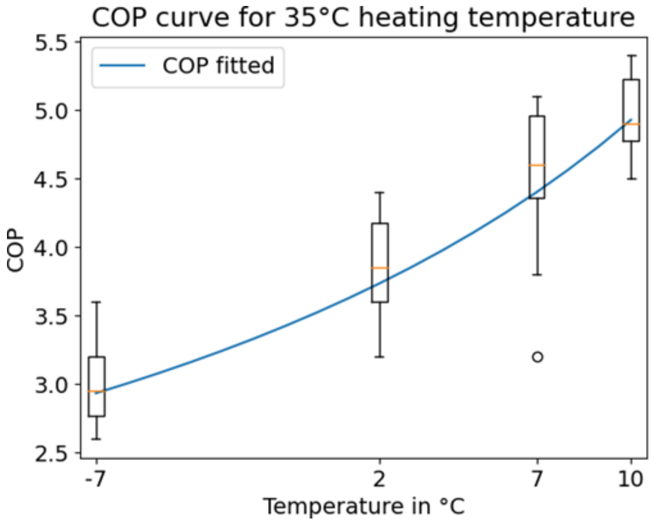


3.1 Heat Pump

The HP is modeled either with an air or ground source heat exchanger. Following assumptions are made to get a linear representation of the HP working conditions: (1) The indoor temperature in the building is homogeneous; (2). The HP's coefficient of performance (COP) is linearly related to the outdoor or ground temperature. Then, the COP of HP is modeled as equation (1), solely dependent on the source temperature (T_t^0) and the supply temperature (T_t^S). η is a constant efficiency factor set to 0.4 for the air HP and 0.35 for the ground source HP.

$$COP_t = \eta \times \frac{T_t^S}{T_t^S - T_t^0} \quad (1)$$

Figure 2: COP curve estimated with Carnot efficiency compared to manufacturer data (Bosch, Viessmann, Daikin, Helios, Ochsner, ed. (n.d.))



The values of η for the air and ground source HP were chosen so that the resulting COP is consistent with the data from various HP manufacturers (Bosch, Viessmann, Daikin, Helios, Ochsner). A comparison of the different COP values from manufacturers and the calculated COP is given in Figure 2. The data from manufacturers is visible as box-plots. An average supply temperature of 35 °C is considered. The ground source HP depends not on T_t^0 but on the temperature below the ground, estimated at 10 °C.

The HP is designed to supply enough heat to a building when the outside temperature is at -14 C. This temperature was chosen because it is just below the typical value for sizing heating systems in Austria. In case of temperatures below -14 °C, we consider a supplementary electric heater (COP = 1). The size of the AC was chosen to be sufficiently large to keep the indoor temperature of the building at a temperature of 27 °C on the hottest day of the year.

3.2 Energy storage

Regarding the storage solutions in the model, we consider a hot water tank for space heating and a battery, which can be implemented with different sizes or not at all. For simplification, assumptions on the heat exchange inside the hot water tank are made so that it doesn't introduce non-linearity to the optimization: (1) The temperature inside the hot water tank is homogeneous; (2) The temperature surrounding the tank is constant at 20 °C; (3) The thermodynamic properties of the water - heat capacity (c_{water}), volume, and pressure - are constant. The hot water storage is modeled with a heat loss coefficient of 0.2 W/m^{2}K. The state of charge (SOC) is determined by the water temperature, which is initially 28 °C. The energy inside the tank ($Q_{tank,t}$) is described through equation (2). The following equations represent the physical limits of the hot water storage.

$$Q_{tank,t} = m_{water} \times c_{water} \times \left(T_{tank,t} - 28\right) \tag{2}$$

$$T_{tank,0} = 28 \tag{3}$$

$$28 \leq T_{tank,t} \leq 45 \tag{4}$$

$$Q_{tank\_loss,t} = 0.2 \times A_{tank} \times (T_{tank,t} - 20) \quad (5)$$

$T_{tank,t}$ denotes the water temperature inside the tank. A_{tank}[3] indicates the surface area of the tank. Only one tank is considered in this analysis with a volume of 1500 liter and a surface area of 7.32 m^2.

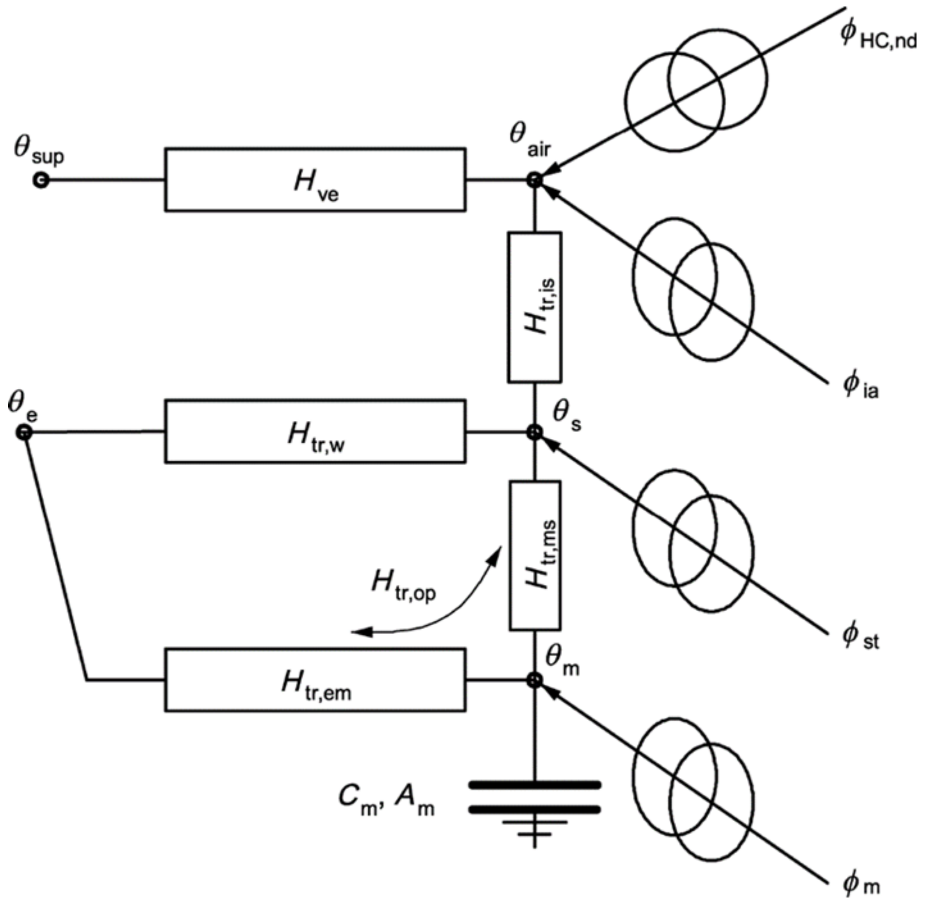
Regarding the battery, we make following assumptions: (1) The input and output power is limited to 4.5 kW; (2) The efficiencies for charging and discharging are equal to 95%. According to Kebede et al. (2021), roundhouse efficiencies of stationary battery storages are reported to be in the range between 78% and 98%. Our estimated round house efficiency of 90.025% is well within this range; (3) The battery is empty at the beginning of the simulation and the capacity of battery is 7 kWh. In Hernández et al. (2019), the optimal battery size for households was calculated to be between 3.6 and 6.9 kWh. Also, Leonhartsberger and Wittmann (2021), who conducted a market analysis on battery storages in Austria, found that the average storage capacity is around 6.7 kWh. We chose 7 kWh for this study.

3.3 Thermal capacity of buildings

The necessary heating and cooling power to keep the indoor temperature at a certain level is calculated with a simplified 5R1C model described in DIN ISO 13790.

[3] A_{tank} is derived from the volume (V) of the tank by calculating the minimal surface area, i.e. $A_{tank} = 2\pi r^2 + 2V/r$, with r being the radius which is calculated by $r = (2 \times V/4\pi)^{1/3}$.

Figure 3: Heat flows in the 5R1C grid (DIN EN ISO 13790)



As shown in Figure 3, the 5R1C model describes a building through an electrical circuit with five resistances and one capacity. The resistances represent thermal transmission coefficients for windows ($H_{tr,w}$), walls ($H_{tr,em}$ for the effective thermal mass and ($H_{tr,ms}$ for the whole surface mass), ventilation (H_{ve}), and a thermal conductance between the indoor air node and the surface temperature node. This model is computationally affordable by simplifying the building's properties and, therefore, can be integrated into an hourly linear optimization algorithm.

Through the 5R1C approach, the model can store energy in the building envelope by pre-cooling or pre-heating the building. The profitability and the amount of stored energy depend primarily on the thermal insulation of the building. While a greater thermal capacity indicates a higher storage potential, a maximum exists where more thermal mass does not result in further storage potential as the heat transfer rate is too low (Chen et al. 2020). In addition, the thermal losses that would occur in a prolonged heating/cooling period would predominate so that it is no longer profitable to cool/heat the house prematurely.

3.4 Running modes

Based on the modules introduced above, our model can run in two modes: optimization and reference. By comparing the results of the two modes, we show the impact of SEMS.

3.4.1 Optimization mode

The optimization was developed in Python with Pyomo (Hart et al. 2017) and solved by Gurobi[4]. The objective is to minimize the household's electricity cost over a whole year as shown by equation (6), with EP_t, $EC_{grid.t}$, FiT, $ES_{pv2grid,t}$ representing the electricity price, grid-electricity consumption, feed-in tariff, and PV-generation sold to the grid, respectively.

$$\min \quad Cost = \sum_{t=1}^{8760} EP_t \times EC_{grid.t} - FiT \times ES_{pv2grid,t} \tag{6}$$

The total grid-electricity consumption consists of all internal loads from appliances ($EC_{app.t}$), heat pump ($EC_{ht.t}$), and cooling ($EC_{co.t}$), minus the consumption supported by PV-generation ($EC_{pv,t}$) and battery ($EC_{battery,t}$) (equation (7)). Besides, the PV-generation ($ES_{pv.t}$) goes to internal loads, grid, or battery (equation (8))

$$EC_{grid.t} = EC_{app.t} + EC_{ht.t} + EC_{co.t} - EC_{pv.t} - EC_{battery.t} \tag{7}$$

$$ES_{pv.t} = ES_{pv2load,t} + ES_{pv2grid,t} + EC_{pv2battery.t} \tag{8}$$

3.4.2 Reference mode

In the reference mode, the input parameters are the same but without optimization. Heating and cooling demand profile are decided by outside temperature, radiation and indoor set temperature. PV- generation is assumed to satisfy electricity consumption of the household directly. The excess generation will be first stored in the battery, then sold to the grid. On the other hand, battery is discharged immediately to cover internal loads if needed. In the reference mode, the thermal mass of the building is considered in the thermal dynamics (captured by 5R1C model) but without being optimized, i.e. pre-heated or pre-cooled. Besides, the hot water tank is not used in the reference mode for simplification[5]. Based on the assumptions above, the self-consumption rates of 5 kWp and 10 kWp PV system without battery are 32.78% and 21.75%, respectively. They will be increased to 47.19% and 31.66% when battery is available. These results are in the range consistent with existing studies (Yildiz et al. 2021; Luthander et al. 2015).

[4] Mathematical programming solver, https://www.gurobi.com/.

[5] With the logic we implemented for the battery, the tank would always be charged in summer with excess PV-electricity, however, it cannot be discharged because space heating is not needed. In the end, this results in high losses and self-consumption rate of PV generation, which is also unrealistic and disrupts the purpose of "reference mode", i.e. serving as the benchmark for comparison. So, for simplification, we don't consider the use of hot water tank in the reference mode.

4 Data and Scenarios

This section presents the exogenous input data shown in Figure 1 and defines the scenarios for further calculations.

4.1 Energy demand of households

For the representative household in our model, three aspects of energy demand are set exogenously: electricity base load profile (from appliances), hot water demand profile, and indoor set temperature.

The electricity base load profile is a synthetic load profile for a single household (APCS, ed. 2019). It is a mean profile of many households. Therefore, it is not representative of a single dwelling. However, our optimization assumes a perfect forecast, which is impossible for electrical loads like cooking or a coffee machine or hot water demand from showering in a single household. Hence, we use these smoothed profiles to prevent the over-optimization for these unpredictable loads.

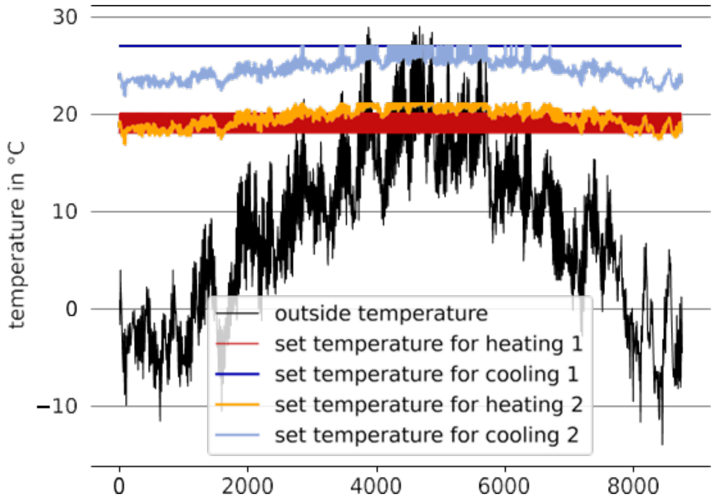
The hot water demand profile shape is taken from the HOTMAPS (Aydemir et al. 2020) project. It is configured to a mean daily consumption rate of 90 liters of hot water in the household (ÖNORM, B, ed. 2019). The natural temperature of the water is assumed to be 10 °C and the supply temperature 55 °C. Thus, the average hot water energy demand is 1725 kWh/year.

At last, two different indoor temperature settings were used in this model. The first is a straight temperature band with a minimum temperature of 20 °C during the day and 18 °C during the night (10 pm to 6 am). The maximum temperature is 27 °C. In the second temperature setting, the minimum temperature is a function of the outside temperature:

$$T_{set,t}^{min} = 20 + (T_t^0 - 8)/8 \tag{9}$$

The maximum temperature is set to the minimum temperature plus 5 °C and capped at 27 °C. Both indoor set temperature bandwidths are presented in Figure 4 together with the outside temperature.

Figure 4: Outside temperature together with the two different indoor temperature settings



4.2 Outdoor **temperature**, radiation, and PV generation

The outdoor temperature and radiation profiles are exogenously derived from PV GIS (Huld et al. 2012). To enhance the quality, we first download the hourly profiles for a whole year at NUTS-3 resolution, then aggregate to the national level by taking the weighted average with regional heat demand as the weights to ensure a descriptive profile for the building stock in Austria. The information on regional heat demand is taken from the HOTMAPS Database (Aydemir et al. 2020). The direct and indirect solar radiation is obtained in every celestial direction on a vertical plane which then will be multiplied with the effective window area of the respective direction to calculate the solar gains.

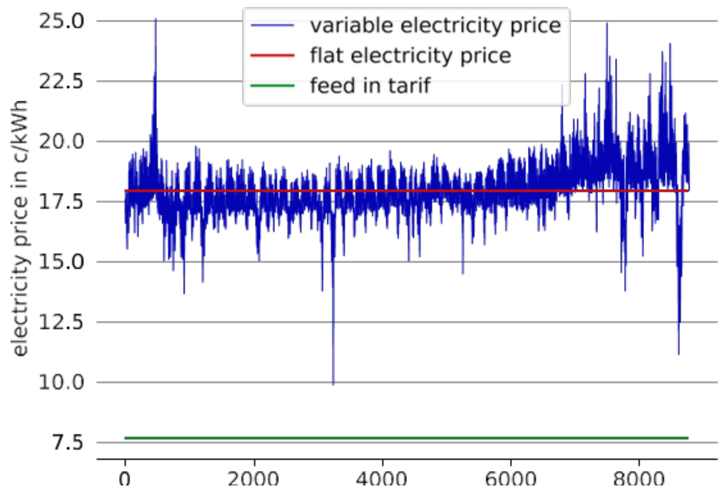
We set the PV sizes at 5 kWp and 10 kWp of crystalline silicon type for the PV generation profile with a system loss of 14%. Hernández et al. (2019) analyzed the optimal PV and battery storage size, taking battery degradation into account, and found that the optimal PV size should be between 1.8 and 2.7 kWp. However, their households did not use HP. Therefore, the electricity consumption per year is significantly lower than the case in our study.

4.3 Electricity price and feed-in tariff

The electricity price is the driving factor in an economic minimization problem. The variable electricity price was taken from EXAA (2016) in 2016 for Austria. We added a fixed grid fee plus taxes of 15 cent/kWh to the variable price to make it a realistic price profile[6]. The flat price was set to the mean value of the variable price to get comparable results when using a flat price in the simulation. The feed-in tariff (FiT) for electricity sold to the grid is constant at 7.67 cent/kWh (E-control 2017). These prices are shown in Figure 5.

[6] The statistical information on this price signal is as follows: mean, 17.9 cent/kWh; maximum, 25.1 cent/kWh; minimum, 9.9 cent/kWh; first quantile, 17.2 cent/kWh; third quantile, 18.5 cent/kWh; standard deviation, 1.2 cent/kWh; variance, 1.3cent/kWh.

Figure 5: Variable and flat hourly electricity price together with the FiT (EXAA 2016, E-control 2017)



4.4 Building parameters and stock data

All building parameters are selected from the INVERT/EE-Lab Database (Müller 2021). In this study, we only consider single-family houses (SFH). 11 different representative building types were selected from the Austrian building stock. Every building type represents buildings built in a specific time period starting from 1890 up to 2011. For buildings built up to 1980, only those buildings that have been refurbished since then are considered. It is unlikely to install HPs in old buildings with insufficient insulation and an old heat distribution system.

Figure 6: Number of selected SFH in this study from the Austrian building stock (Müller 2021)

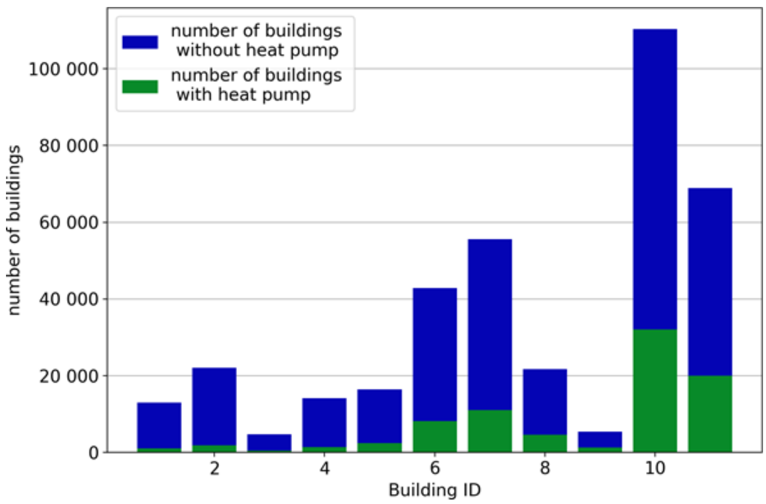


Figure 6 illustrates the number of buildings of all 11 categories and the share of buildings using a HP for heating. Information on each building category is provided in Table 2.

There are around 1.55 million SFH in Austria and 119 397 PV installations with an average capacity of 5.7 kWp (Statistic Austria, O, ed. 2021). The number of buildings we consider in this study is 375 282. Since 2011, around 120 000 SFH were built, and as we estimate, 33% of them were built with a PV. That leaves approximately 80 000 PV installations for buildings up to 2011, where we assume that a large margin (90%) was installed in renovated or buildings built after 2000. Therefore, the percentage of SFH with a PV installed is 19% for the buildings we consider. 17.6% are 5 kWp installations and 1.4% are 10 kWp installations.

According to Leonhartsberger and Wittmann (2021), a total number of 21 838 batteries were installed in Austria's residential homes in combination with a PV since 2014. We estimate that around 67% of those are installed in newly built buildings (after 2014). No numbers are available before 2014, as batteries were too expensive and not established in the market. Thus, 2% of the buildings considered in this work have a battery installed in combination with a PV.

The total amount of sold small-scale thermal storages is not reported anywhere for the case of Austria. Most HPs have been installed in combination with a small domestic hot water storage. In this paper, we use the estimation that 60% of all buildings with a HP considered in this work also have a thermal storage. Out of the 375 282 buildings, 84 712 have a HP. To show the potential of SEMS, we assume that all buildings considered in this study with a HP are being optimized. 25% of all HPs in Austria are ground sourced (Emhofer et al. 2014).

4.5 Scenarios

To cover as many sensitivities and possibilities as well as influential factors, we established various household parameters for all representative buildings. The following dimensions capture each case: (1) Technology, including hot water tank, battery, PV size, etc. resulting in 96 configurations for each SFH (Table 1); (2) Building, including 11 representative SFH and their standard heating demand calculated based on ÖNORM (2019) (Table 2); (3) Electricity price, including flat and variable price. In total all 96 configuration options were applied to the 11 building types. The resulting 1056 households were run with both electricity prices resulting in a total of 2112 simulations in optimization and reference mode.

Table 1: Technology configurations

Technology	Parameter Values
Hot water tank	0 liter, 1500 liter
Battery size	0 kWh, 7 kWh
PV size	0 kWp, 5 kWp, 10 kWp
HP type	air source, ground source
Cooling	adopted, not adopted
Indoor temperature	fixed temperature range, smart temperature rang

Table 2: Building IDs with average floor area (Af) and useful energy demand for space heating (ÖNORM, B, 2019)

ID	Type	Age Class	A_f (m^2)	Useful demand for space heating (W/m^2)
1	SFH	1890-1918	129	161.8
2	SFH	1890-1918	129	132.1
3	SFH	1919-1944	136	160.2
4	SFH	1919-1944	136	146.2
5	SFH	1945-1960	144	136.1
6	SFH	1961-1970	154	105.9
7	SFH	1971-1980	163	105.9
8	SFH	1981-1990	166	93.4
9	SFH	1991-2000	170	88.9
10	SFH	2001-2008	170	69.1
11	SFH	2009-2011	170	69.1

5 Results

This chapter compares the results of optimization and reference modes to show the impact of SEMS. First, taking an individual building perspective with different households' configurations, Section 5.1 analyzes the impact of SEMS on energy consumption, including grid-electricity demand and the self- consumption of PV. Then, based on a detailed construction of the building stock in Austria, Section 5.2 investigates the impact of SEMS on the total energy consumption at the national level.

5.1 Impact on individual households

Figure 7 shows the result from both reference and optimization modes under a flat electricity price. First, as shown in the top-left plot, buildings with better insulation demand less electricity from the grid, and optimization can further reduce this amount. The maximum annual decrease of grid-electricity consumption through SEMS is 40.69%, which is found for a well-insulated building (ID = 11) equipped with a 10 kWp PV (no battery), an AC, a ground source HP, and thermal storage. Second, the adoption of PV significantly reduces the grid-electricity consumption, and the larger size of PV leads to lower grid- electricity demand (up-right). Third, as shown in the left bottom plot, the thermal storage has limited impact on the optimization results. The key reason is that, when the radiation is higher in summer, space heating is not needed, so the optimization will not save the excess PV-generation in the tank. The thermal tank is only used by the buildings with 10 kWp PV systems because they generate enough electricity to be stored in the tank in winter. In the reference mode, the thermal storage is not being used, hence the results are identical. The use of the battery (bottom right) results in much lower electricity demand in the reference mode as most of the surplus electricity can be stored and used. In the optimization mode, the difference is not significantly visible because the optimization can also utilize other storage potentials (eg. pre-heat/cool the building) when no battery is available.

Figure 7: Impact of SEMS on PV self-consumption rate of individual households (flat price).

The height of the violin represents the distribution. The width represents the density of plotted results for different households.

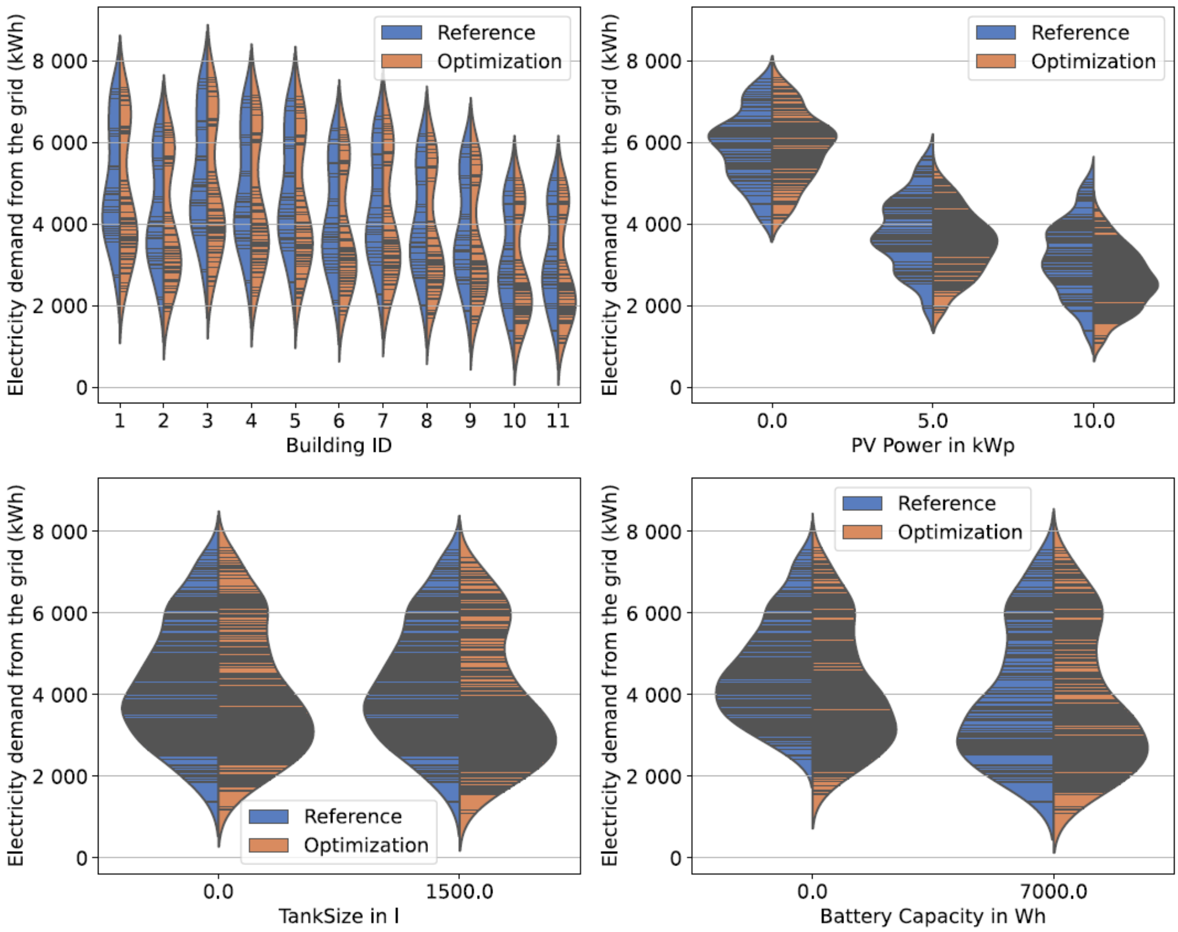
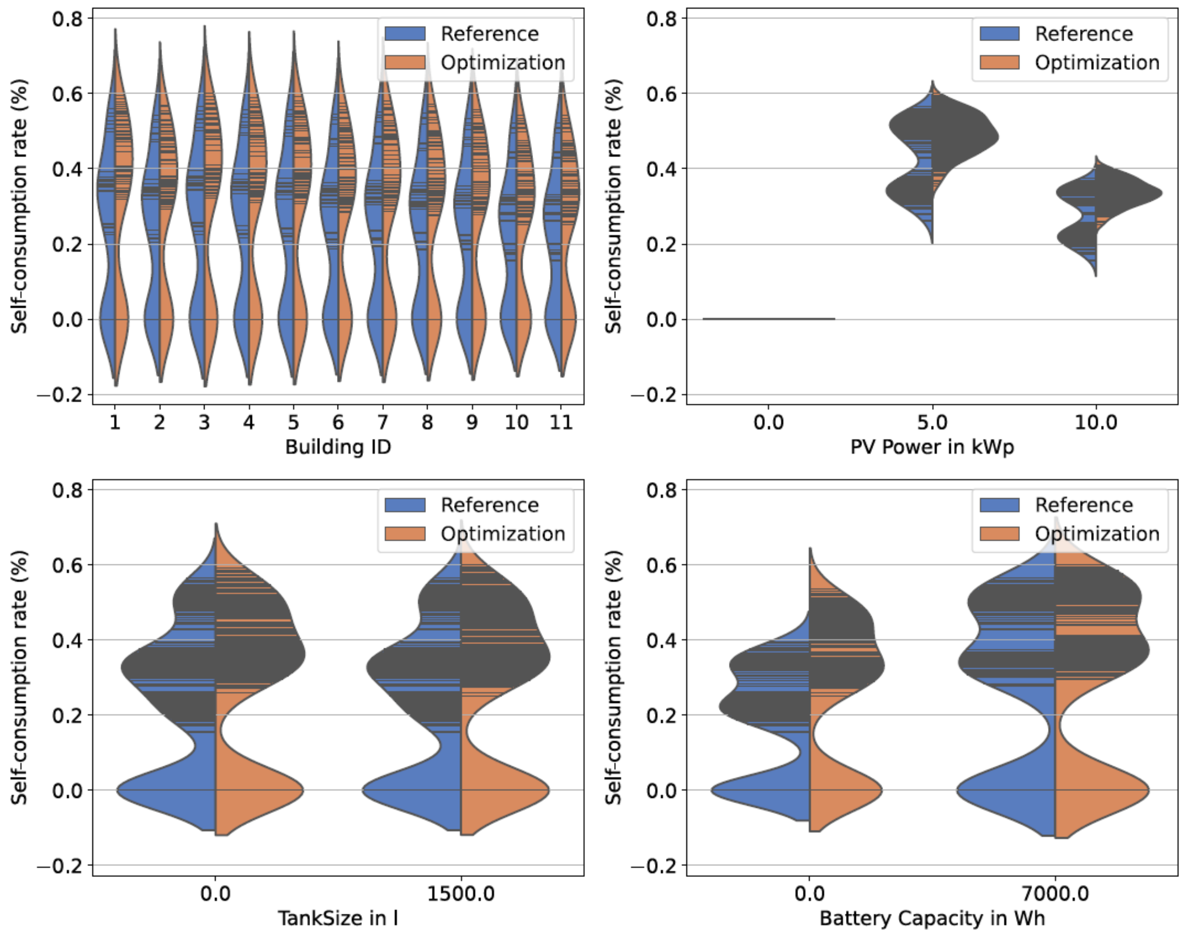


Figure 8 illustrates the PV self-consumption rate for all 2112 simulations under reference and optimization modes. Obviously, the self-consumption rate is zero for all household configurations that do not have a PV system. It is also visible that optimization improves the self-consumption rate to a specific threshold where it is more profitable to sell instead of saving the electricity. With a 10 kWp PV, the overall consumption rate drops compared to the 5 kWp PV because electricity surplus cannot be utilized. Again, the impact of thermal storage on self-consumption rate is limited in the optimization.

On the other hand, under variable price, SEMS can further improve the profitability of a given technology configuration by using more electricity to pre-heat the hot water tank when the price is lower. However, this difference is not visible when comparing all possible configurations at the same time. Therefore, this comparison is provided at an aggregated level in Section 5.2

Figure 8: Impact of SEMS on PV self-consumption rate of individual households (flat price)



Furthermore, concerning the configurations of indoor set temperature and HP source, the calculations show that their impacts are limited:

First, the mean difference among all 2112 calculations in electricity consumption from the grid between the two indoor set temperature functions was 0.42%, 2.59%, and 2.61% for the reference, the flat price optimization, and the variable price optimization, respectively. With the second indoor set temperature, the demand increased compared to the first set temperature. The optimization pronounces the difference meaning that the first indoor set temperature function has a higher potential to reduce electricity demand from the grid. The price signal has virtually no influence.

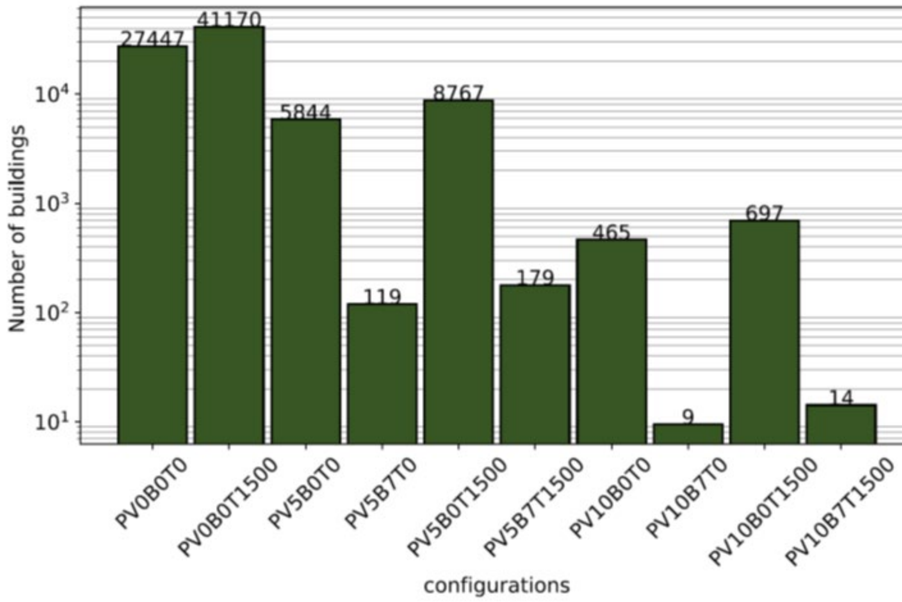
Second, the ground source HP reduces grid demand by 22.55%, 21.79%, and 22.2% in reference, the flat price optimization, and the variable price optimization compared to the air source HP. Hence, we can deduce that the optimization has minimally more impact on buildings with an air source HP. This was expected as the optimization algorithm can utilize the change in COP with an air HP.

Third, when an AC is implemented, the grid demand rises by 2.73%, 2.31%, and 2.27% in the reference, the flat price optimization, and the variable price optimization.

5.2 Impact on the national electricity system

Following the assumptions made in Section 4.4 on the distribution of technologies in the buildings stock, Figure 9 shows the total number of buildings with a HP and a specific technological configuration: PV size with 0, 5, or 10 kWp; Battery (B) size with 0 or 7 kWh; Hot water tank (T) size with 0 or 1500 liter. The majority of the buildings do not have a PV, and only 23 buildings have a 10 kWp PV and a storage.

Figure 9: Number of buildings in the three scenarios with different technical configurations



The number of buildings with the specifications shown in Figure 9 are broken down by percentage into the individual building classes. Subsequently, the results are calculated for all building classes with the respective specifications in the optimization and reference mode.

The resulting electricity demand is shown in Figure 10. The bars represent the total electricity demand from the grid on a logarithmic scale. The percentage change in grid-electricity consumption through the optimization of each configuration is shown on the right-hand axis for both price scenarios. The absolute values of these percentages are presented in Table 3. Buildings with no PV and no storage don't change their consumption with a flat price signal. But they increase their consumption by 1.02% with a variable price. Thus, the variable price gives the incentive to use the building mass as thermal storage to shift heating load and reduce energy cost. The grid-electricity consumption is reduced by 7.39% and 17.88% for a 5 kWp PV and a 10 kWp PV (flat price) and by 7.22% and 17.75% (variable price), respectively, without any storage implemented. This highlights the potential of utilizing thermal mass as storage. As mentioned in Section 5.1 the variable price leads to a higher utilization of the thermal storage to bridge high prices and thus the percentage decrease of electricity consumption is less for those houses. In total, the optimization can lower the annual grid-electricity demand by 10.4 GWh or 6.8 GWh for the whole investigated building stock under the flat and variable price scenarios, respectively.

Table 3: Grid-electricity consumption increase and decrease for buildings with certain configurations (unit: MWh)

Building configuration	Flat [MWh]	Variable [MWh]	Building configuration	Flat [MWh]	Variable [MWh]
PV0B0T0	0	1451	PV0B0T1500	-3682	-1886
PV5B0T0	-1587	-1551	PV5B7T0	-5	1
PV5B0T1500	-4275	-3946	PV5B7T1500	-32	-22
PV10B0T0	-270	-268	PV10B7T0	-1	-1
PV10B0T1500	-574	-555	PV10B7T1500	-4	-3

Figure 10: Impact of SEMS on grid-electricity consumption of the building stock

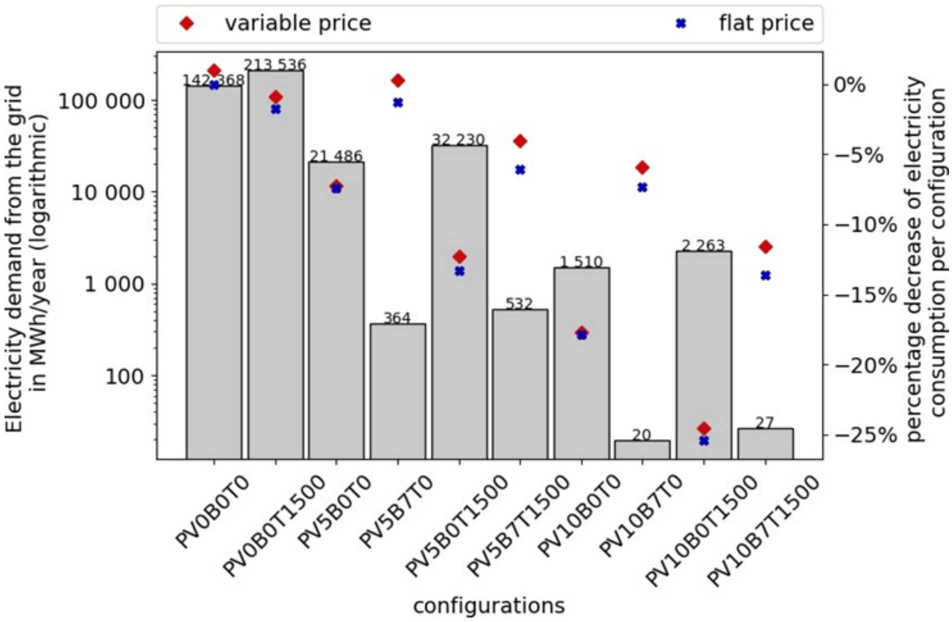
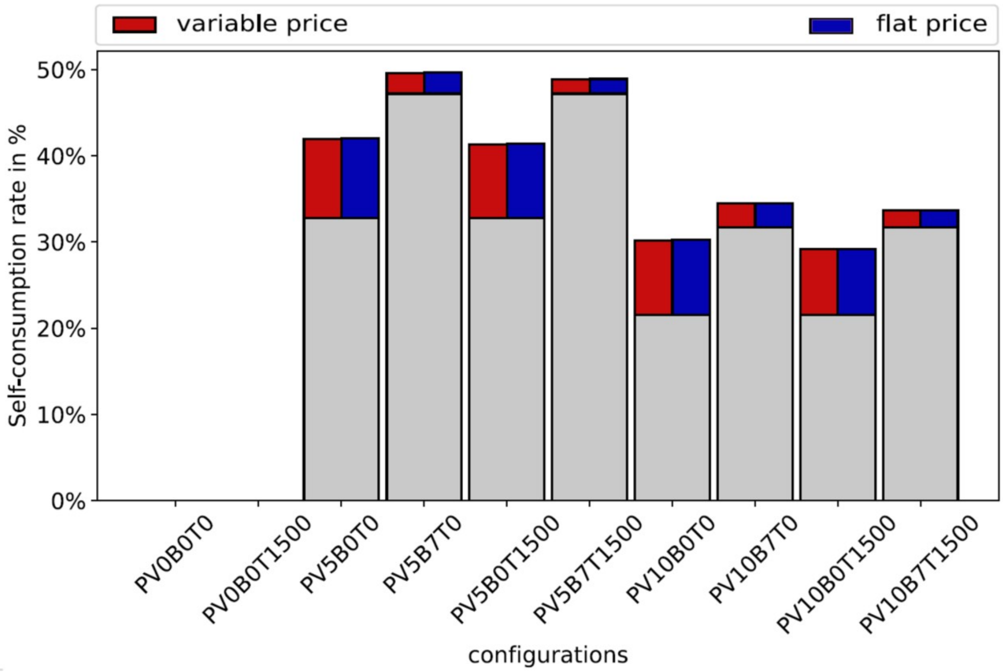


Figure 11 shows the aggregated self-consumption rate of buildings with different configurations. The grey bars represent the results from the reference mode. In the reference mode the consumption rate for buildings with PV and no battery storage are the same since the thermal storage is not utilized in the reference mode as introduced in Section 3.4.2. Buildings with a thermal storage show almost the same increase in self-consumption rate as buildings without a thermal storage. Again, buildings without the thermal storage utilize the building mass instead. For buildings with a battery storage, the SEMS does not result in such a high increase in self-consumption because the battery already increases self-consumption significantly in the reference mode. The difference in self-consumption increase between the flat and the variable price signal is minimal.

Figure 11: Impact of SEMS on PV self-consumption rate of the building stock



6 Conclusions

Promoted by the Renewable Energy Expansion Act and declining PV and battery prices, the number of prosumagers in Austria is expected to grow. This study evaluates how such change can impact the electricity consumption of the residential sector at both individual household and national levels. Starting with a detailed hourly model which can be run with both optimization and reference modes, we comprehensively evaluated 2112 cases of representative households. Furthermore, we aggregated the results of individual households to the national level based on detailed modeling of the SFH stock in Austria and evaluated the impact of SEMS at a national level. Two policy scenarios are also considered: flat and variable electricity price.

First, we found that SEMS can significantly increase the self-consumption of PV-generation, regardless of the building typology and configuration. Here we highlight the usage of building mass as thermal storage. For the buildings with 5 kWp PV system and without any storage, SEMS can decrease the overall electricity demand from the grid by 1.5 to 1.6 GWh in Austria. Second, the application of variable electricity price can further facilitate the load-shifting significantly, by pre-heating or pre-cooling the building, when SEMS is implemented. So, from a sector coupling perspective, time variable electricity pricing could be a promising option for policy design. However, pre-heating the building when the electricity price is lower may also lead to higher losses from the thermal mass, which means higher electricity consumption. A comprehensive analysis on the impact of variable electricity price is still needed. At last, SEMS can also impact the investment decision of a household. However, this paper only considers the "operation" of the household energy system and provides limited implication for investment decisions. This topic will be covered in our further studies.

This paper has the following limitations. First, the building stock data only covers buildings up to 2011, which we plan to update in further steps of this research. Also, we did not yet consider the possible evolution of the building stock and installed heat pumps and other technologies in the coming years and decades. Second, as Kotzur (2018) mentioned, the 5R1C model can overestimate the cooling demand, which needs further analysis and calibration. An evaluation of the load profiles and peak loads will follow. However, in Austria, SEMS has limited effects on cooling consumption, especially compared with heating. Therefore, it won't influence the main findings of this study. The variable price signal did make the usage of thermal mass lucrative for homeowners. However, a further sensitivity study on the volatility of the price signal can be conducted. Third, Battery degradation was not included in the optimization algorithm. By including battery degradation, the optimization will have a different impact on buildings with a battery concerning consumption behavior as well as cost reductions.

Author contributions

Conceptualization – Philipp Mascherbauer, Lukas Kranzl, Songmin Yu, and Thomas Haupt; Methodology, formal analysis, writing – Philipp Mascherbauer, Songmin Yu, and Thomas Haupt; Supervision and review – Lukas Kranzl, Songmin Yu; Methodology review and editing – Lukas Kranzl and Songmin Yu. All authors have read and agreed to the published version of the manuscript.

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