FlexMyHeat

D1.1 – Characterization of flexible assets, adoption potential and grid constraints and markets

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Table of Acronyms and Definitions

2R2C	2-state resistance-capacitance
BAU	Business-as-Usual
BESS	Battery Energy Storage System
COP	Coefficient of Performance
DBSCAN	Density-Based Spatial Clustering of Applications with Noise
DHI	Diffuse Horizontal Irradiance
DHW	Domestic Hot Water
DNI	Direct Normal Irradiation
DSO	Distribution System Operator
GHI	Global Horizontal Irradiance
GTI	Global Tilted Irradiance
IOT	Internet of Things
NACE	Nomenclature statistique des Activites economiques dans la Communaute Europeenne
PCA	Principal Component Analysis
PCM	Phase Change Material
PV	Photo Voltaics
PVGIS	Photovoltaic Geographical Information System
SCOP	Seasonal Coefficient of Performance
SGD	Stochastic Gradient Descent
SH	Space Heating
SOC	State of Charge
TMY	Typical Meteorological Year

I. INTRODUCTION

The FlexMyHeat project aims at understanding the role that heat pumps and decentralized storage solutions will play in 2030 and 2050 as a source of flexibility for the national electricity system.

By 2050 heat pumps will provide between 35% and 95% of the Belgian demand for heat. This might turn to +50% of the Belgian peak load, but this extra burden on the electricity system could be turned into an opportunity by properly controlling these heat pumps in combination with local storage solutions.

This will result in several advantages:

- Significant reduction of peak loads
- Increase of self-sufficiency of Belgium
- The power grid will become more resilient

The main objectives of the FlexMyHeat project are:

1. **Assess the impact and value:** Assessment at national level, of the electrification of the heat demand via heat pumps, in 2030 and 2050. Heat pumps in combination with PV are seen both as an additional burden to the system (higher demand, higher decentralized production), and as a new flexibility resource to balance the Belgian electricity system by exploiting their flex through appropriate and practical control strategies. Furthermore, the project analyzes the potential of decentralized storage solutions (electrical and thermal) to complement the flexibility of heat pumps.
2. **Take the full picture:** FlexMyHeat wants to understand the impacts of local grid constraints and upcoming local contractual frameworks (energy communities) on the above mentioned flexibility potential. This leads to additional elements, in the form of Local Restrictions constraining the maximal flexibility potential due to:
   - Operational limits imposed by the local grid operator (e.g. peak shaving)
   - Financial interests of the local contractual framework (e.g. cannibalization of flexibility by local contracts/self-sufficiency)

   These elements will be taken into account and the limits at national level will be assessed.
3. **Adapt the market:** FlexMyHeat will propose demand response programs, as well as adapted flexibility services that can exploit the capabilities of the decentralized energy resources. This will include the proposition and quantitative evaluation of appropriate coordination mechanisms and associated control algorithms, at the various relevant timescales.

FlexMyHeat will quantitatively evaluate these objectives using 3 scenarios:

- **Business-as-usual:** considering the heat pumps and possibly associated local storage as independent devices (i.e., no dynamic interaction from the grid side to exploit their flexibility) and controlling devices using simple rule-based logics.
- **Unconstrained flexibility exploitation:** this considers maximal adoption of the flexibility opportunities offered by the heat pump and storage devices, ignoring potential local grid constraints
- **Flexibility operation with local restrictions:** this will consider the “full picture” and thus combine the various flexibility incentives/mechanisms driven by the grid with local objectives.

This deliverable describes the results for the first (Business-as-usual) scenario.

The deliverable is structured as follows:

- **Section II** describes the different data sources that were used for the analyses.
- In **Section III** we describe the analysis of these data sources and their clustering, to derive representative users for the detailed evaluations.
- In **Section IV** the modelling of the relevant assets (building environment, heat pump, battery and thermal storage) is detailed.
- Finally, in **Section V**, we describe the results for the Business-as-usual scenarios.

II. Data Description

II.1. Load Data

As part of the FlexMyHeat project, the consumption profiles of low-voltage network users were analyzed. For this purpose, ORES provided consortium members with actual offtake and injection profiles based on quarter-hourly readings taken via smart meters. As a reminder, these meters are installed to replace the old-generation wheel meters. They are very useful for the DSO, as they provide a more accurate view of the network, thanks to measurements of energy (active and reactive), voltage, current, etc.

It's also important to note that the meter only measures what leaves or enters the meter. In other words, the DSO has no knowledge of internal flows behind the meter, such as prosumer self-consumption.

In all, there are over 950 sampling profiles containing data for a full year. These profiles are varied: business and residential customers, prosumers and non-prosumers, single-rate or dual-rate customers, electric and non-electric vehicles, prepayment customers, different localities, etc.

In Wallonia, declaring your charging station is a legal obligation imposed by the decree of April 12, 2001 on the organization of the regional electricity market. Any installation or de-installation of a charging station must be reported to the relevant grid operator. This provision does not yet exist for heat pumps, and it is therefore impossible for the DSO to know whether or not the customer has a heat pump.

However, more than a year ago, ORES launched a statistical survey of some smart meter customers on their heating habits, so we have precise information for those customers who responded to the questionnaire. This information, together with other technical/contractual information (connection power, gas density at connection point, zip code, customer type, type of connection), has been provided to the consortium.

Thus, thanks to contractual/technical data as well as sampling and 1/4h injection data, it was possible to carry out various analyses, in particular to confirm that the synthetic profiles developed via the model are similar, on average, to the actual profiles of users of the low-voltage distribution network.

II.2. Heat Pump Data

In this section, we describe the origin and characteristics of the data used for heat pumps in the project. The primary source of the data is ***heatpumpmonitor.org***, an open-source platform that collects real-time performance data from various heat pump installations across different households, predominantly in the UK. This dataset offers detailed insights into the operational performance of heat pumps, which is critical for evaluating their potential contribution to electrical flexibility in the Belgian grid.

II.2.1.a. Data Sources

The data is accessible in both raw and pre-processed formats, stored on Heatpumpmonitor.org and available through CSV files and BigQuery. The data used in the project includes various metrics from each heat pump installation, helping to monitor its performance in different operational conditions. Pre-processed data is available to streamline the analysis. Figure 1 shows an example of available data on heatpumpmonitor.

Figure 1 Typical example of available data for a heatpumpmonitor installation

II.2.1.b. Core Data Features

Features unit can vary from one installation to another. Not all the features below are available on every installation.

Feature	Description	Unit	Remarks
heatpump_flowT	Water flow temperature leaving the heat pump	°C	Directly measured
heatpump_returnT	Water return temperature returning to the heat pump	°C	Directly measured
deltaT	Difference between flow and return temperature	°C	Represents thermal performance and heat exchange
COP	Coefficient of Performance (Heat produced / Electric power consumed)	-	Calculated from heatpump_heat and heatpump_elec
heatpump_heat	Heat produced by the heat pump (often for space heating and DHW combined)	W	Measures the heat output
heatpump_elec	Electrical power consumed by the heat pump	W	Directly measured, used for COP calculations
heatpump_dhw	Heat produced exclusively for domestic hot water	W	DHW-specific heat production
flow_rate	Flow rate of the heating circuit (regulated by the heat pump)	L/min or m³/h	Usually measured in L/min, varies between installations
T_setpoint	Setpoint temperature for the water leaving the heat pump	°C	Inferred from heating curve and external temperature
mode	Operational mode of the heat pump (e.g., heating or standby)	-	Varies by installation, not universally available
control	Indicates whether the heat pump is on (1) or off (0)	Boolean	Computed, based on electricity consumption
dhw	Indicates if the heat pump is producing domestic hot water	Boolean	Computed, if flow temperature > 40°C
T_DHW_mid, T_DHW_top, T_DHW_bottom	Temperatures at various positions (middle, top, bottom) of the DHW tank	°C	
T_ambient	Outdoor temperature	°C	Not always available on HPM
T_indoor	Indoor temperature, typically in the living area near the thermostat	°C	Not always available oN HPM
setpoint	Desired indoor temperature	°C	Rarely available, but helps align with user preferences
humidity	Indoor humidity level	%	
PV	Electricity produced by solar panels	W or kW	Not always available
elec	Total electricity consumption of the household	W	
grid	Electricity imported from or exported to the grid	W	Net metering data from the house's smart meter
battery	Electricity stored from solar panels in home battery storage	W	Not always present

II.2.1.c. Data Collection and Pre-Processing

The raw data is collected and stored in CSV format, with pre-processing conducted to ensure it is clean and ready for analysis. This process involves:

1. **Data Cleaning:**
    a. Removal of negative heat values and unrealistic temperatures (e.g., temperatures above 100°C).
    b. Handling missing values through interpolation and resampling data to a 1-minute interval.
    c. Detection and removal of outliers and irregularities, with special handling for sparse data.
2. **Feature Engineering:**
    a. Creation of additional control features (e.g., whether the heat pump is on or off based on electricity consumption).
    b. Development of metrics for cumulative operation time and differentiation between DHW and space heating modes.
    c. Calculation of setpoint temperatures using weather-compensated heating curves based on ambient temperature.
3. **Scenario Development:**
    a. The data is processed and divided into different test scenarios, which include analyzing operational efficiency, calculating potential grid flexibility, and understanding user behavior.
    b. These scenarios are essential for simulating and forecasting the heat pump’s contribution to grid flexibility and energy consumption optimization.

To effectively evaluate the heat pump's performance, the data undergoes a thorough pre-processing and feature engineering workflow. This structured approach ensures the reliability and relevance of the data for scenario analysis.

1. **Data Loading:**
   The raw data is imported from BigQuery, which houses all heat pump performance records.
2. **Selection of Relevant Columns:**
   Only the necessary columns related to the heat pump’s thermal and electrical performance, along with environmental conditions, are selected for further processing.
3. **Data Pre-Processing:**
    - **Missing Values Analysis:** The dataset is examined to identify any missing values, with the number of missing entries assessed on a daily basis.
    - **Data Visualization:** All relevant data points are plotted to detect outliers and irregularities that may impact the analysis.
    - **Outlier and Error Detection:** Suspicious data points, such as negative heat values or temperatures exceeding 100°C, are identified and removed.
    - **Normalization:** Where applicable, an upper limit is imposed on heat production and electricity consumption, which varies depending on the specific heat pump model.
    - **Resampling:** The data is resampled to uniform 1-minute intervals, and the mean values are computed to smooth out any fluctuations.
    - **Index Correction:** Duplicate indexes are removed to maintain data integrity.
    - **Interpolation of Missing Values:** For datasets with significant missing data, values are interpolated to fill the gaps. This is particularly important for sparse data.

- **Dropping Irrelevant Rows:** Rows containing only NaN (Not a Number) values are discarded, as they do not provide useful information.
- **Indoor Temperature Interpolation:** For cases where indoor temperature data is missing, interpolation methods are used to estimate these values.

4. **Feature Engineering:**
    - **Control Feature:** A control feature is created based on the electricity consumption of the heat pump, indicating when the heat pump is operational.
    - **Cumulative Operation Time (control_cumul):** This feature tracks how long the heat pump has been running continuously, offering insights into operational patterns.
    - **Operational Status (keep):** A 'keep' feature is added to indicate whether the heat pump was on during the current or previous time step, improving event tracking.
    - **Domestic Hot Water (DHW) Indicator:** A feature is created to differentiate between the production of hot water and space heating, based on flow temperature thresholds.
    - **Setpoint Temperature (T_setpoint):** The setpoint temperature is calculated based on the heating curve, which is weather-compensated and determined through a linear regression of outdoor temperature against water flow temperature.

This systematic process ensures the data is clean, reliable, and ready for the development of test scenarios. By engineering key features and applying rigorous pre-processing, the data can be used to simulate the performance of heat pumps and their role in providing grid flexibility.

II.2.1.d. Conclusion

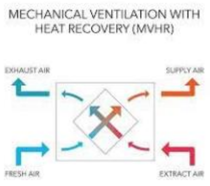
The rich dataset provided by Heatpumpmonitor.org offers an extensive view of heat pump operation in real-world conditions. With detailed features ranging from thermal output and electrical consumption to environmental conditions and system performance, the data forms a solid foundation for assessing heat pump performances. The pre-processing steps ensure data integrity, allowing for accurate and actionable insights to be derived in the project's ongoing analysis.

II.3. Residential Indoor Temperature Data

Residential Indoor Temperature Data are historical data from 41 apartments building in Nivelles – Wallonia where IoT devices were installed and monitored since 2021. Figure 2 demonstrates an example of extracted indoor temperature data for an apartment.

The following information is available:

- Apartments data: floor level, number of bedrooms, surface
- IOT data from individual mechanical ventilation equipment taken every 5 min in each apartment



TEx = Extracted indoor air temperature

TSu = Supplied air temperature

HuEx = Extracted indoor air relative humidity

HuSu = Supplied air relative humidity

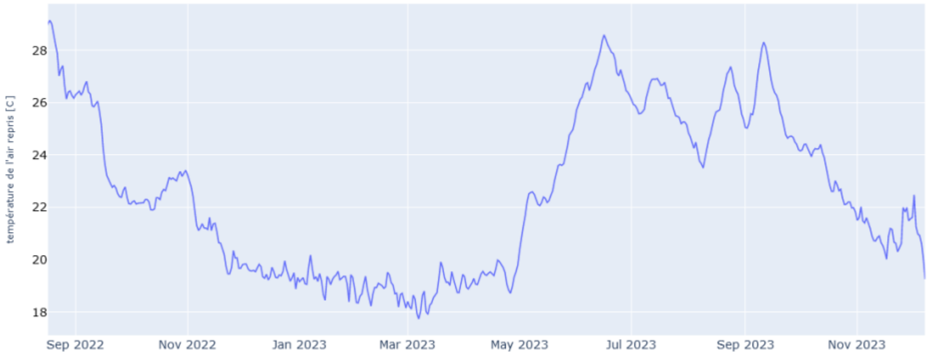


Figure 2 Sample of extracted indoor temperature for 1 apartment

These data will be used for smart control scenarios and more specifically, scenarios with heat pumps.

II.4. Meteorological Data

Meteorological data are needed to obtain accurate PV generation profiles and for a realistic control of the heat pumps based on the outside temperature. The data were collected from the Solcast website[1], providing historical weather information from 2007 up to now, with a 5-minute time resolution. We chose 5 different locations in Belgium, namely Antwerp, Bütgenbach, Lessines, Marche-en-Famenne, and Nivelles, to account for regional diversity in the study. For each location, we collected the following data for the period 2021 to 2024: temperature, diffuse horizontal irradiance (DHI), direct normal irradiation (DNI), global horizontal irradiance (GHI),

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

global tilted irradiance (GTI), wind direction and wind speed at 10m and 100m above ground level.

II.5. Electricity Tariff

In general, a customer's energy bill is divided into several components:

- the network component (distribution and transmission)

- the energy component (electricity)

- taxes, surcharges, VAT, etc.

Each region (Flanders, Brussels and Wallonia) has its own regulator, and tariffs differ from one region to another, making the world of energy quite difficult to master.

Historically, the 3 regions had both single-rate and dual-rate tariffs. The dual-rate tariff was developed to encourage customers to consume energy at night, when excess electricity from nuclear power plants is available.

But today, it's not the same story, as consumption now has to be adapted to the intermittent nature of renewable energy production. This is the case, for example, with small-scale local photovoltaic production, which will produce electricity and inject in the grid at the same time as soon as there's a ray of sunshine. It's also about making the best possible use of public distribution infrastructures and reducing our demand of power from the grid.

One way of achieving these two objectives is to use implicit flexibility, which simply consists of encouraging customers to modify their consumption behavior in response to a price signal, which may concern the network component and/or the energy component. To respond to the price signal, the customer may use automatic means to activate these loads, but this is not part of the context of implicit flexibility.

Network component

Given the different regulators and the sometimes divergent visions of network tariffs, each region has a specific tariff and a different vision of time.

For example, since January 1, 2023, Fluvius in Flanders has introduced a capacity tariff for residential customers, to encourage them to reduce their peak electricity demand on the grid.

At Sibelga in Brussels, a tariff based on contractual connection power (below or above 13 kVA) has also been introduced, to encourage customers to moderate power increases in particular.

Finally, in Wallonia, ORES and the other DSOs (RESA, AIESH, AIEG and REW) will introduce new incentive tariffs from January 1, 2026. These new tariffs consist of three prices that differ according to the day:

- from 5pm to 10pm: red hour tariff
- from 7 a.m. to 11 a.m. and from 10 p.m. to 1 a.m.: orange hour rate
- from 1 a.m. to 7 a.m. and from 11 a.m. to 5 p.m.: green hourly rate.

As you can see, each DSO/regulator has a different view of tariffs, which doesn't make things easy. Each type of tariff structure (fixed, capacity, proportional, with or without time slots, etc.) has its advantages and disadvantages.

Energy component

Each supplier can also offer different commercial packages, including a “dynamic” contract in which the energy price varies from hour to hour. This tariff can be interesting if you have flexible loads that you can easily modulate, such as an electric vehicle, battery or heat pump.

As part of the FlexMyHeat project, we plan to produce tariff simulations that take these different tariffs into account. It should be noted, however, that comparisons should be made with caution, as the rate calibration assumptions between Wallonia, Brussels and Flanders are not identical! In principle, however, the simulations include a capacity tariff to see how the heat pump can be made flexible to respond to an ELIA tariff signal, while incorporating load modulation to optimize the Fluvius capacity tariff.

III. DATA ANALYSIS

III.1. Clustering Load Data

The goal is to cluster households based on their energy consumption profiles, making the analysis and interpretation of the load data easier. The resulting clusters can be used to sample representative users from each cluster, ensuring diversity and generalizability in the study.

III.1.1. Clustering Method

We used a three-stage clustering approach [1], as outlined in Figure 3. The main advantage of this approach is that it is completely unsupervised and does not rely on any predefined load conditions, such as splitting load profiles into weekends and weekdays.

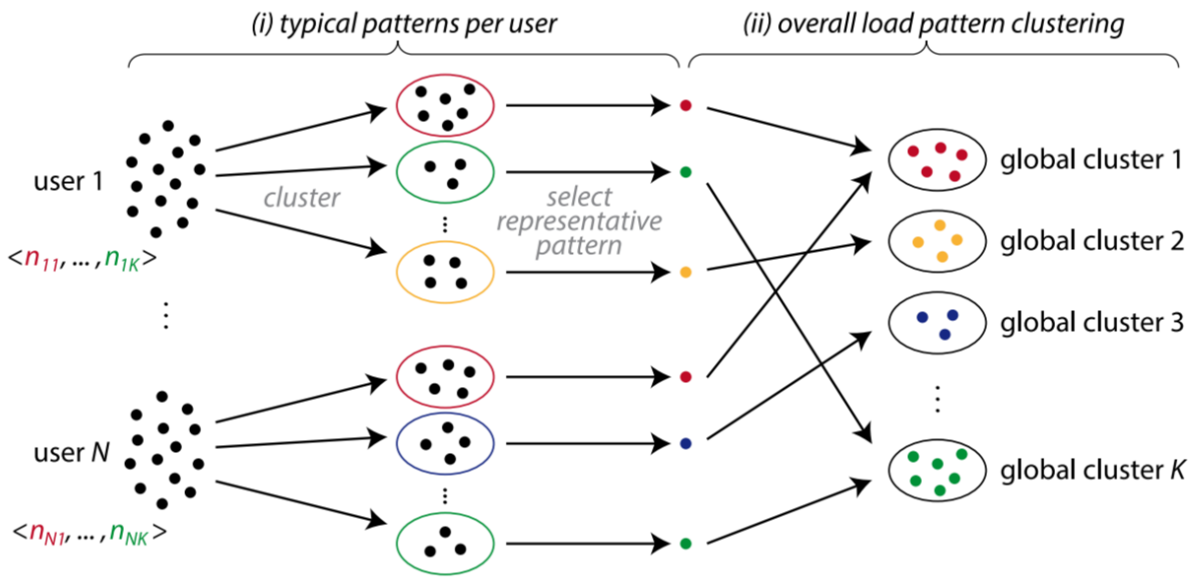


Figure 3 clustering methodology

The main stages of the clustering approach are as follows:

- In the first stage, daily load patterns of a single user are clustered and a representative day for each cluster is selected.
- In the second stage, these representative days for all users are clustered resulting in global clusters.
- Finally, in the third stage, users are clustered based on their membership to these global clusters.

All stages employ the same clustering algorithm, namely the K-means clustering method, to process the set of load patterns they take as input. Residential and commercial load patterns are clustered separately to more effectively extract representative users for both sectors from the dataset.

III.1.2. Clustering Results for Residential Loads

Figure 4 shows the clustering result for stage 2. The grey lines show the individual day profiles. The red line is the centroid profile of the cluster, and the blue lines are real samples that are closest to the centroid. We tried several numbers of clusters, ranging from 4 to 20. We obtained the most intuitive result when the number of clusters was set to 9. This figure shows the general residential load patterns that exist in the dataset. For example, the middle and bottom left profiles illustrate a typical household profile with an evening peak.

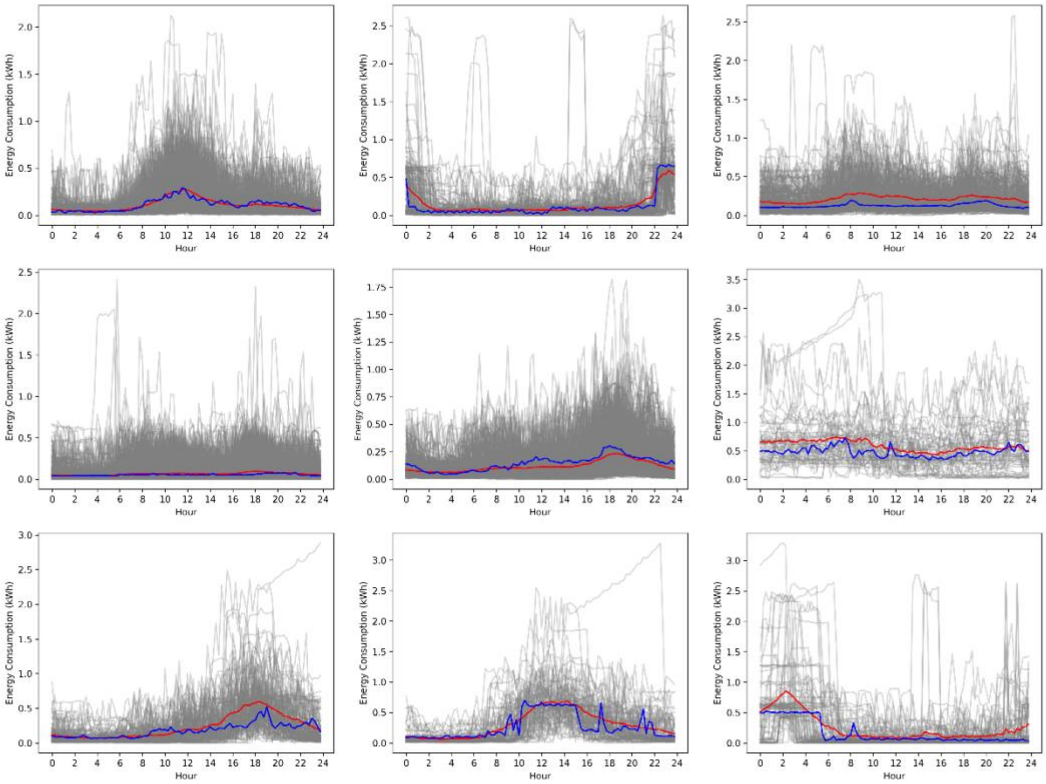


Figure 4 clustering results of residential users for stage 2

For clustering residential users in stage 3, first, a Principal Component Analysis (PCA) was applied to the data to reduce the dimensionality of the dataset from 9 (cluster counts) to 2. Afterward, the density-based spatial clustering of applications with noise (DBSCAN) clustering was applied. The result is shown in Figure 5. The number of final clusters was 9.

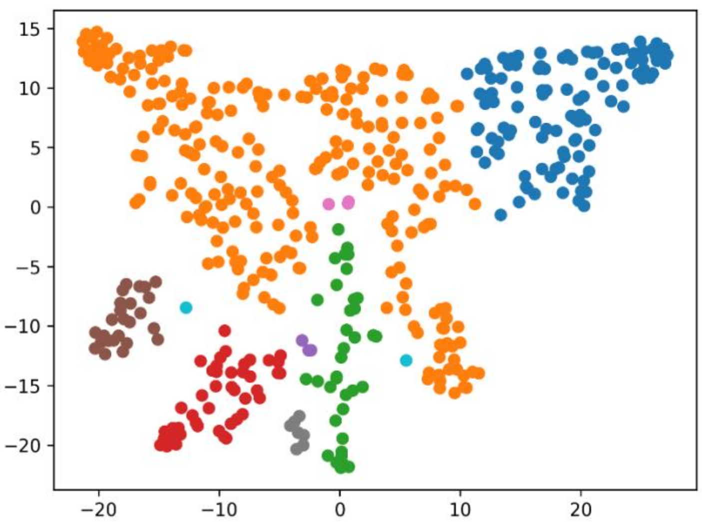


Figure 5 Results for clustering residential users

III.1.3. Clustering Results for Commercial Loads

Figure 6 shows the clustering result of commercial users for stage 2. We tried several numbers of clusters, ranging from 4 to 16. We obtained the most intuitive result when the number of clusters was set to 9. Since we have NACE codes for some commercial users, we cross-checked our obtained global clusters with these codes to ensure that we have typical expected load profiles. For example, the middle right profile illustrates a typical workplace profile, such as that of a municipal government (gemeentelijke overheid).

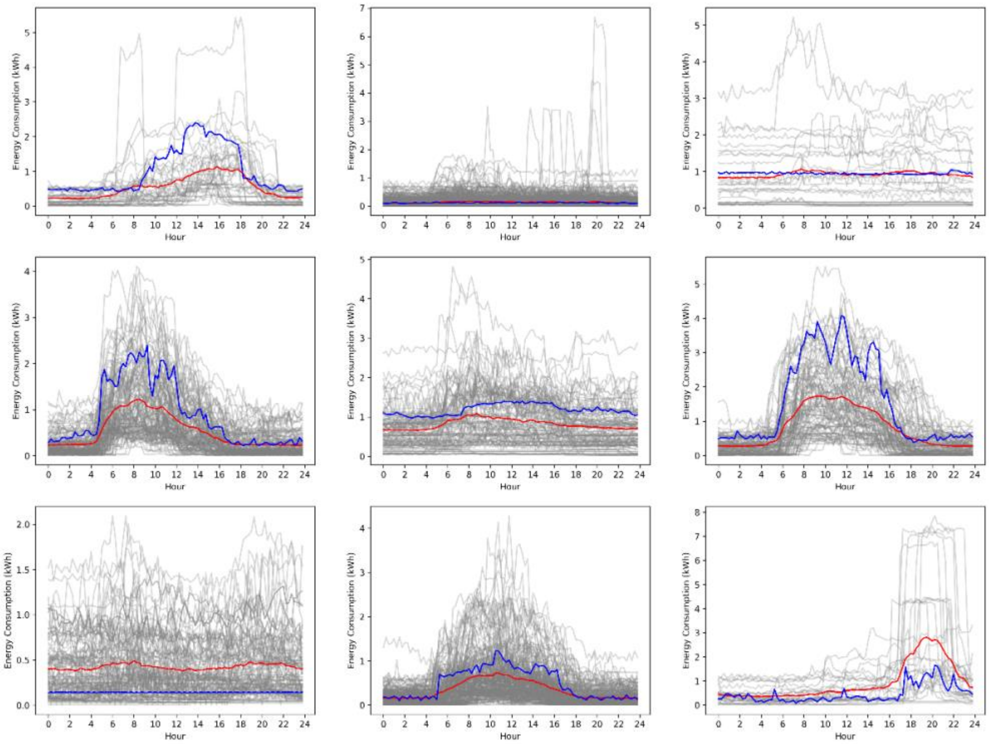


Figure 6 clustering results of commercial users for stage 2

We cluster the commercial users in stage 3 in a similar way as the residential users, as shown in Figure 7. The number of final clusters was 7.

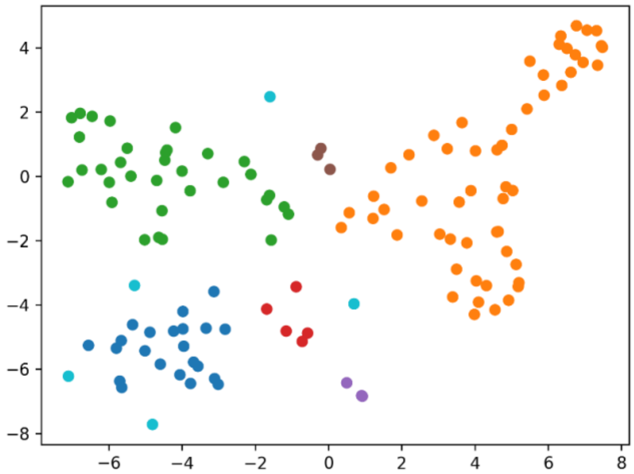


Figure 7 Results for clustering commercial users

III.2. PV Generation Estimation

In order to characterise the photovoltaic production, it is important to use the same weather data as those used for the heat pump modelling. Therefore, we have used data from the European platform "*Photovoltaic Geographical Information System" (PVGIS)*, via the Python library called "*pvlib*".

With the *pvlib* library, we were able to generate production profiles (normalised per kWp installed) based on real historical weather data obtained via "*solcast*" for the years 2021 to 2023. These weather data include air temperature, direct and indirect solar irradiation and wind speed, with a 5-minute timestep.

We obtained 5-minute production profiles, for a set of 15 configurations which are defined by **3 characteristics: location, orientation[2] and tilt**, as following:

- 5 locations
  - Antwerp
  - Butgenbach
  - Lessines
  - Marche-en-Famenne
  - Nivelles

- 3 different combinations of orientation and tilt
  - South orientation and tilt of 30°
  - South-West orientation and tilt of 30°
  - Both East and West orientations and tilt of 15°
  (with 2 rows of panels placed against each other)

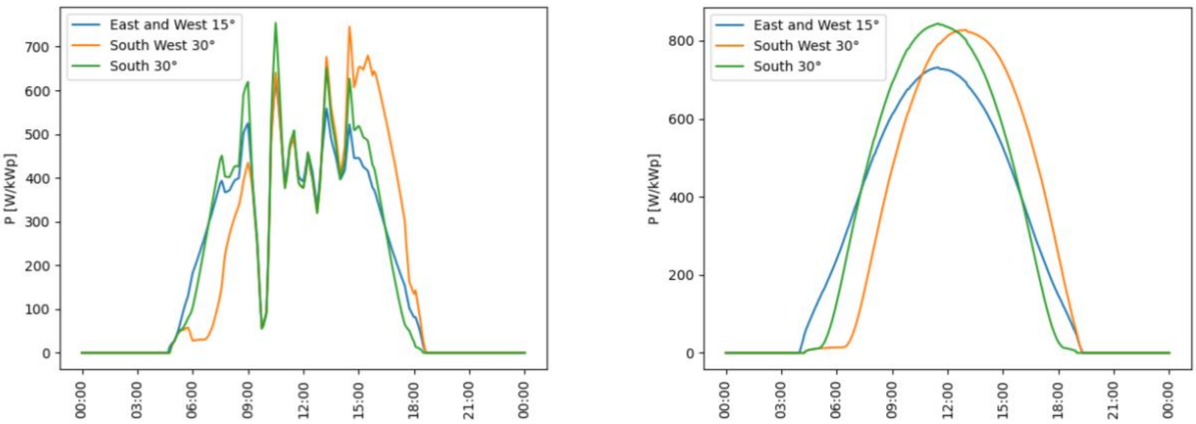


Figure 8 PV production on a cloudy day (left) and on a day with clear sky (right) in Antwerp

These configurations allow to represent both a variety of climates in Belgium, as well as different PV designs which impact the production profiles over a year. A PV installation with a South orientation and 30-degrees tilt will have its production more concentrated in the middle of the day than an East and West 15-degrees tilt configuration. There is also a difference with seasons, as the angle of incidence with the sunlight is also different and impacts the solar production.

For the 2030 and 2050 scenarios, we have used Typical Meteorological Year (TMY) data, calculated on the period 2005-2020 and according to the PVGIS methodology. Instead of averaging yearly data, which would create a huge loss of variability for the data and thus not

[2] Orientation is also called « azimuth »

be realistic, the TMY method is more robust: for each of the 12 months, the most typical month is selected based on a set of meteorological parameters, as the figure here below shows. The TMY is thus a combination of historical months from different years and provides more realistic production data.

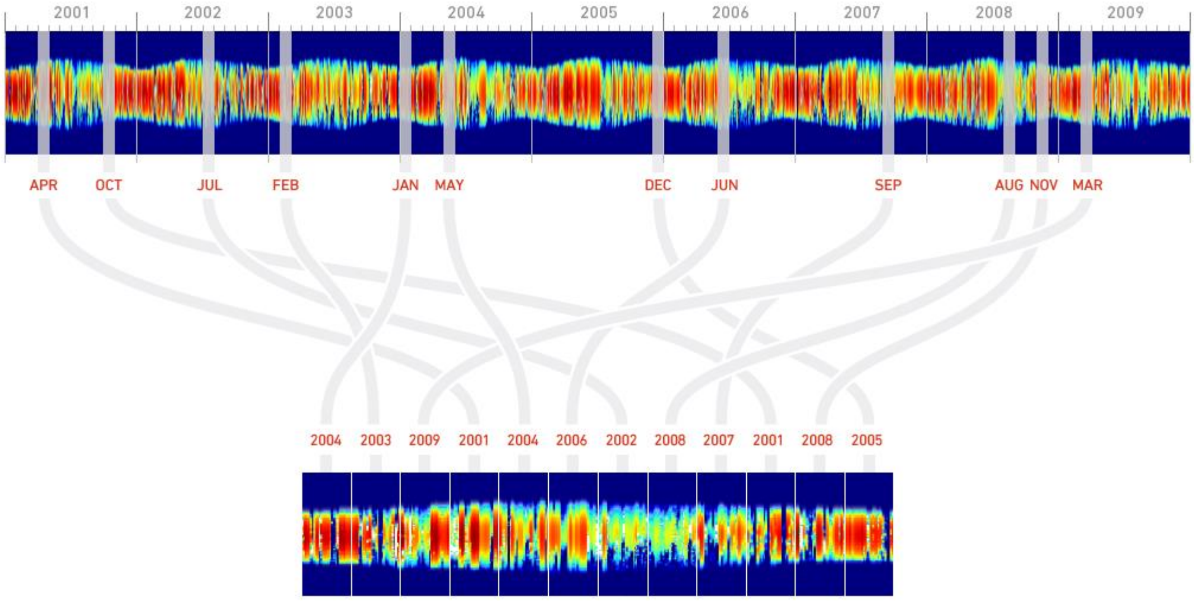


Figure 9 Approach for the construction of a Typical Meteorological Year

IV. Modeling Assets

IV.1. Battery

A battery is a reservoir of energy. It can charge using electric power so as to discharge later, providing electric power.

The model of a battery can be very complex however as the focus of the study is not on battery themselves, we have modelled considering the following characteristics:

- Rated power: this is the maximum rate at which it can charge and discharge. It is given in W (or kW). Typical range is between 3kW and 10kW.
- Capacity: this represents the maximum amount of energy that can be stored in the battery. This is given in Wh (or kWh). Typical range is between 5kWh and 40kWh with majority of batteries being on the lower end of the range.
- Round-trip efficiency: this represents the fact that a battery loses power every time it is charging or discharging.
- Idle lost: this represents the fact that an idle battery loses power.

IV.2. Heat Pump

The **heat pump** is modeled with a constant yearly Seasonal Coefficient of Performance (SCOP). In reality, the COP depends on several factors, such as the water supply temperature and the outside air temperature. For simplicity in this first stage of the project, an annual SCOP has been considered throughout the year.

In order to obtain more realistic results in the future, we will be able to adjust the COP model to take into account the operating conditions of the heat pump.

The **heat pump power** for this model typically ranges between 2 and 5 kW (electrical input), translating to around 5-15 kW (thermal output). The heat pump's evaporator fan power, or possibly the water circulator power, contributes approximately 2% of total consumption, with the compressor remaining the most demanding component.

To ensure reliable and efficient operation, control constraints are applied:

- A minimum off time of 10 minutes is enforced after each shutdown.
- A minimum on time of 15 minutes is required to avoid short cycling.

Modern heat pumps modulate the compressor power, yet this power cannot be controlled by an external signal, except through modulation of the heat demand. For now, the control utilizes simple on/off signals, allowing for straightforward integration into the overall system.

IV.3. Thermal Storage

The **thermal storage** is based on a phase change material (PCM) technology, with a capacity range between 6 and 15 kWh (thermal). Two distinct power outputs are modeled: 35 kW for Domestic Hot Water (DHW) and 5 kW for space heating. This configuration enables high-capacity heating while maintaining efficient storage.

It is modeled as a tank connected to the heat pump with a fixed annual COP, while its charging power is limited by heat pump maximum thermal power.

Thermal storage has a **round-trip efficiency** that accounts for idle losses at a rate of 0.0055% per minute with respect to capacity, resulting in an approximate 1% loss of cell capacity over three hours. No exchange losses are assumed, enhancing overall efficiency.

The **state of charge (SoC)** of the thermal storage can vary between 0% and 100%, with cycles restricted to a maximum annual number to ensure PCM longevity. Each cell is structured to achieve 5000 to 10000 cycles, with two cells allocated for space heating (SH) and two for DHW. To minimize PCM degradation, each cycle must be fully completed (i.e., charged or discharged). The state of the battery is limited to 0%, 50% (1 cell fully charged), or 100% (2 cells fully charged), prioritizing longevity with a 50-50 cell capacity distribution; however, this structure can be adjusted based on specific use cases.

IV.4. Building Thermal Model

Buildings are modeled using a 2-state resistance-capacitance (2R2C) network illustrated in Figure 10.

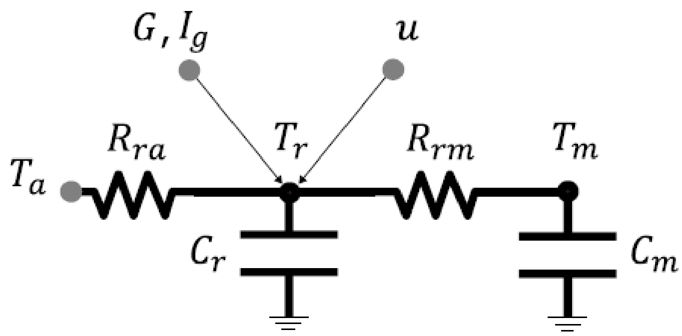


Figure 10 The 2R2C network thermal model of the building

The state-space formulation of the model is written as follows [2]:

$$\begin{bmatrix} \dot{T}_r \\ \dot{T}_m \end{bmatrix} = \begin{bmatrix} -\left(\frac{1}{C_r R_{ra}} + \frac{1}{C_r R_{rm}}\right) & \frac{1}{C_r R_{rm}} \\ \frac{1}{C_m R_{rm}} & -\frac{1}{C_m R_{rm}} \end{bmatrix} \begin{bmatrix} T_r \\ T_m \end{bmatrix} + \begin{bmatrix} \frac{1}{C_r} \\ 0 \end{bmatrix} P + \begin{bmatrix} \frac{\alpha}{C_r} & \frac{\beta}{C_r} & \frac{1}{C_r R_{ra}} \\ \frac{1-\alpha}{C_m} & \frac{1-\beta}{C_m} & 0 \end{bmatrix} \begin{bmatrix} G \\ I_g \\ T_a \end{bmatrix}$$

where T_r, T_m, and T_a are the room, building's thermal mass, and outside temperature, respectively. G and I_g are solar irradiation and internal heat gains, respectively. R_{ra} represents the thermal resistance between the room and the ambient, R_{rm} is the thermal resistance between the room and the thermal mass, and C_r and C_m indicate the thermal capacitances of the room and the thermal mass, respectively. The objective is to estimate R_{ra}, R_{rm}, C_r, and C_m for modelling the building.

The model formulation is discretized as follows:

$$\begin{bmatrix} T_{r,k+1} \\ T_{m,k+1} \end{bmatrix} = \begin{bmatrix} 1 - \Delta t(x_0 + x_1) & \Delta t x_1 \\ \Delta t x_2 & 1 - \Delta t x_2 \end{bmatrix} \begin{bmatrix} T_{r,k} \\ T_{m,k} \end{bmatrix} + \Delta t \begin{bmatrix} x_3 \\ 0 \end{bmatrix} P_k + \Delta t \begin{bmatrix} \frac{\alpha}{C_r} & \frac{\beta}{C_r} & x_0 \\ \frac{1-\alpha}{C_m} & \frac{1-\beta}{C_m} & 0 \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ T_{a,k} \end{bmatrix}$$

To obtain x_i, we define a regression problem as follows [3]:

$$\min_{x_0,x_1,x_2,x_3} \sum_k (\hat{T}_{r,k+1} - T_{r,k+1})^2$$

$$s.t. \quad \begin{bmatrix} \hat{T}_{r,k+1} \\ \hat{T}_{m,k+1} \end{bmatrix} = \begin{bmatrix} T_{r,k} + \Delta t \left(T_{a,k} - T_{r,k}\right)x_0 + \Delta t \left(\hat{T}_{m,k} - T_{r,k}\right)x_1 + \Delta t \; P_k x_3 \\ \hat{T}_{m,k} + \Delta t \; (T_{r,k} - \hat{T}_{m,k})x_2 \end{bmatrix}$$

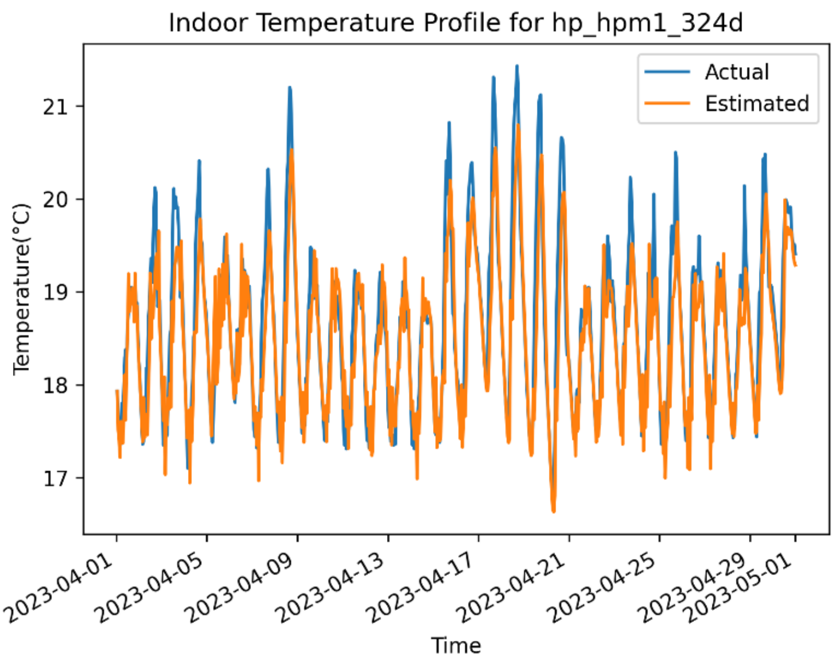
$$x_0, x_1, x_2, x_3 \geq 0$$

$$0.01T_{r,k} \leq \hat{T}_{m,k} \leq 2.5T_{r,k}$$

$$\hat{T}_{m,0} = T_{r,0}$$

The regression problem is a nonlinear optimization problem. We used the stochastic gradient descent (SGD) approach to solve the optimization problem and estimated the thermal parameters for three different buildings. The floor areas of these buildings are 100 m², 75 m², and 134 m². Two of them are from before 1900, while the other is from between 1940 and 1982. The types of buildings are detached, semi-detached, and terraced. We used two months of data, from February 2023 to April 2023, to approximate the parameters. The time interval Δt is set to 1 hour.

To evaluate the performance of the estimated building model, the actual and estimated indoor temperature for the three buildings are shown in Figure 11. For all three buildings, the estimated indoor temperatures successfully follow the trend of the actual indoor temperatures, proving that our building model is accurate.



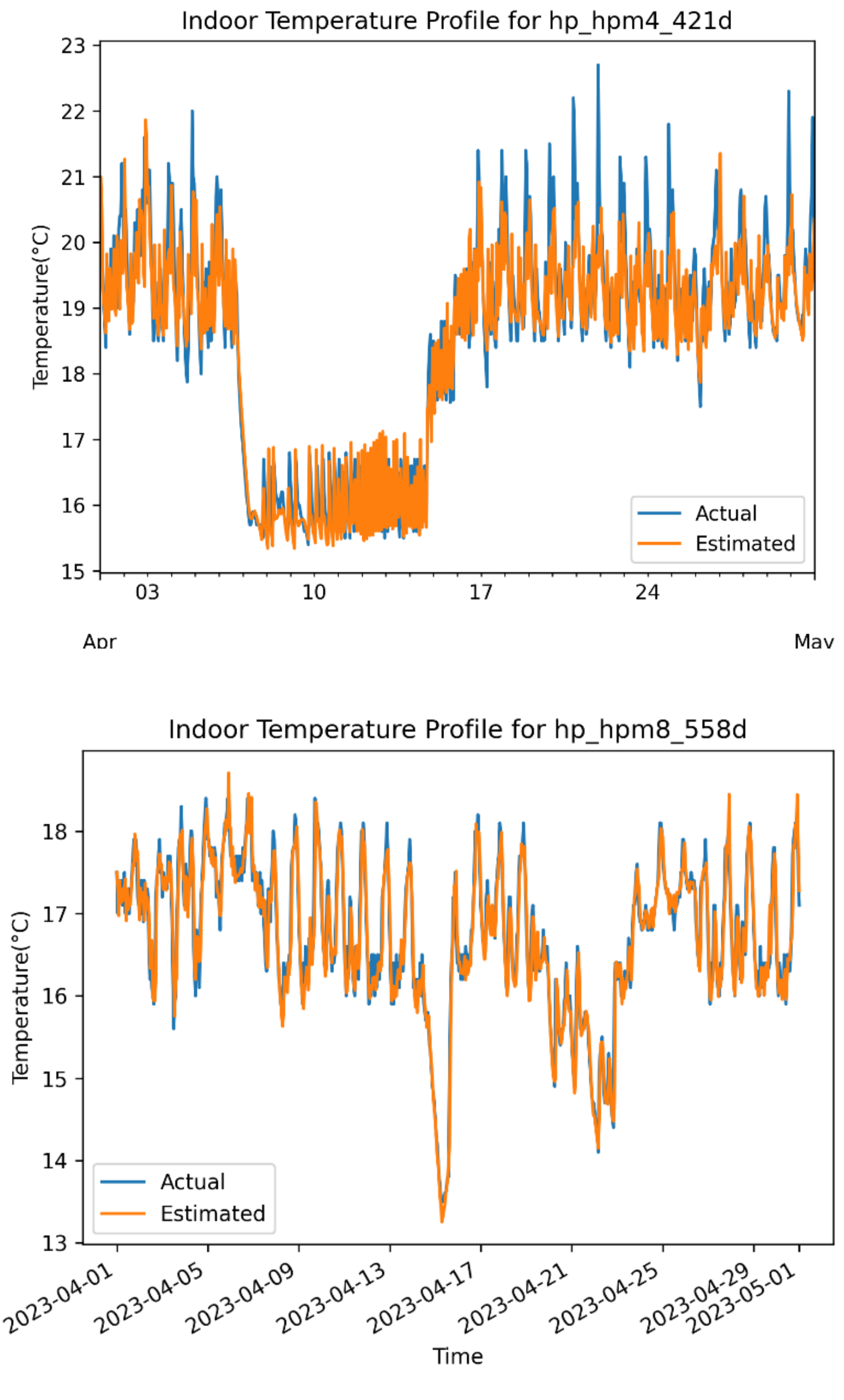


Figure 11 Estimated and actual indoor temperatures for three buildings

Table 1 shows the overview of the average estimation loss on the test data and obtained parameters.

Table 1 average estimation loss and estimated thermal parameters for three buildings

Building	***MAE***	x_0	x_1	x_2	x_3
Type 1	0.31	4.3098e-06	1.3752e-04	2.1239e-03	2.2924e-08

Type 2	0.41	8.9158e-06	2.2360e-03	2.0524e-03	4.1005e-08
Type 3	0.17	3.0178e-06	5.4590e-06	3e-07	1.4124e-08

V. Business-as-usual Scenarios

This section aims to study the effect of increased deployment of heat pumps and decentralized electrical/thermal storage in 2030 when controlled using rule-based business-as-usual control logics. We begin by analyzing the current situation, followed by studying the 2030 scenario, taking into account the estimated evolution of load, price, and the deployment of flexible assets.

V.1. Case Study Description

After clustering users according to the method described in Section III.1, we sampled 24 users from all clusters, with at least one from each cluster. We chose 5 different locations in Belgium to ensure diversity in weather and PV generation. We selected the load profiles of users without PV and calculated PV generations to them. For the sizing of these PVs, we used annual production data from users with almost the same annual consumption and scaled the PV generation based on this value. For each location, we considered the sampled 24 users including 10% Gaussian noise. So, in total, we studied 120 households across 5 different locations in Belgium. For each household, the PV generation is calculated based on Section III.2. We randomly assigned the estimated building models from Section IV.4 to these 120 households. Price tariffs are explained in detail in Section II.5.

There are three sources of flexibility in this study: heat pumps, batteries, and thermal storage. We used three different types of heat pumps with nominal heating powers of 3.5 kW, 5 kW, and 5 kW, and coefficient of performances (COP) of 4.14, 3.89, and 4.26, respectively. The minimum on and off times for all heat pumps are 15 minutes and 10 minutes, respectively. We considered five different batteries with the following characterization: 3 kW/5 kWh, 5 kW/8 kWh, 5 kW/10 kWh, 5 kW/12 kWh, and 10 kW/20 kWh, all having a round-trip efficiency of 96% and an idle loss of 0.00168% per minute. We employed three different thermal storage systems with the following characterization: 5 kW/3.5 kWh, 5 kW/6.5 kWh, and 5 kW/9.8 kWh, each with a COP of 4, 2 cells, and an idle loss rate of 0.0055% per minute.

Based on a study conducted by ORES on the evolution of electricity consumption in Wallonia by 2030, load growth is projected to be around 55%. Therefore, we applied the same ratio to project the load profiles for 2030. For predicting PV generation in 2030, we applied TMY weather as explained in detail in Section III.2. According to a flexibility study conducted by Elia, the average day-ahead price is expected to be 82 €/MWh by 2030 [4]. Since the average day-ahead price in 2023 was 97.4 €/MWh, the price evolution ratio is set at 0.84.

V.2. Business-as-usual Scenario Definition

The business-as-usual (BAU) scenarios are defined as follows:

- Base scenario: load profile with PV without any flexible asset
- Scenario 1: base scenario with battery
- Scenario 2: base scenario with heat pump
- Scenario 3: base scenario with heat pump and thermal storage
- Scenario 4: base scenario with battery and heat pump
- Scenario 5: base scenario with battery, heat pump, and thermal storage

The rule-based BAU controller for electrical/thermal storage aims to maximize self-consumption by charging the storage when there is excess PV generation and discharging it when there is a shortage of PV generation. The rule-based BAU controller for heat pumps ensures user thermal comfort by maintaining the indoor temperature within a defined range ([18 ℃, 22 ℃]).

V.3. Results for 2023

For 2023, since the penetration of heat pumps is low, we only studied the base scenario and Scenario 1. Figure 12 shows the average daily peak power spread across all households.

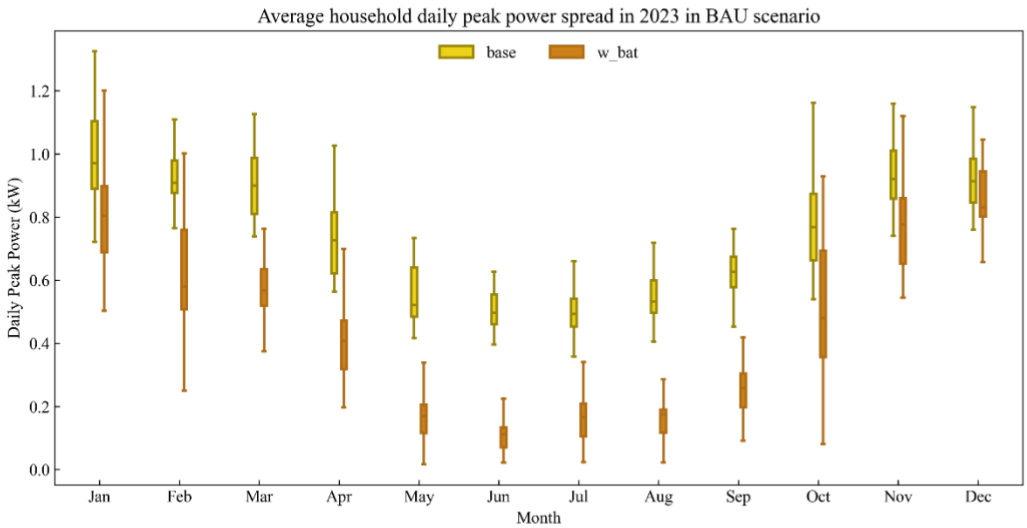


Figure 12 Average household daily peak power spread in 2023

The results show that adopting batteries reduces the household daily peak power on average by 0.3 kW. The reduction is larger during the summer due to increased PV generation, allowing the batteries to better flatten the load profile.

The average offtake energy profile across all households is illustrated in Figure 13. Batteries flatten the offtake profile by storing energy during the day when there is high PV generation and self-consuming the stored energy in the evening. Based on the 25% quantile profile, after adding batteries, households in about 25% of the time have zero offtake energy. In other words, in 25% of the time, households are independent of the main grid.

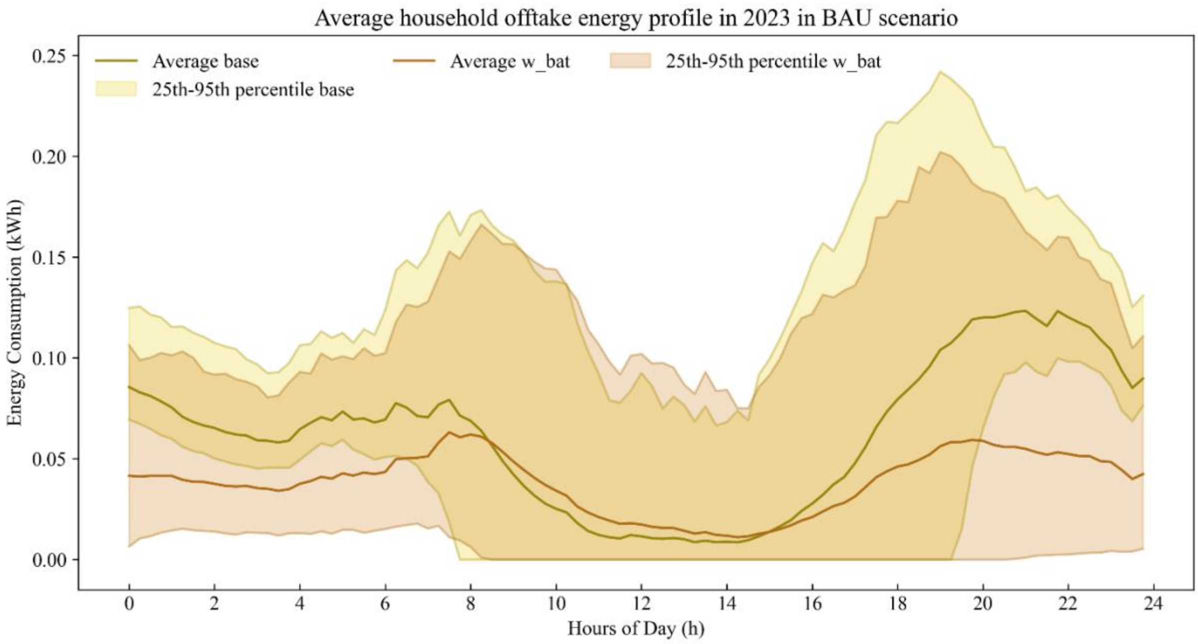


Figure 13 Average household offtake energy profile in 2023

Table 2 provides an overview of the average annual electricity bill across all households for various price schemes. Users will incur the highest costs when exposed to dynamic prices. Batteries could help reduce the annual electricity bill on average by 140.85 €. The reason is that in the evening, when prices are high, the battery supplies energy to the household, allowing them to avoid purchasing electricity at high prices.

Table 2 Overview of the average annual electricity bill in 2023

DSO	Supplier	Base (€)	S1 (€)
Single-hourly tariff - ORES	Single-hourly tariff	359.35	212.66
	Day-ahead price	406.33	242.01
Bi-hourly tariff - ORES	Bi-hourly tariff	334.37	199.74
	Day-ahead price	369.37	219.97
3-level tariff - ORES	3-level tariff tariff	360.54	205.21
	Day-ahead price	384.35	221.71
Capacity tariff - Fluvius	Single-hourly tariff	243.83	145.77
	Day-ahead price	291.89	176.13

The average monthly electricity bill across all households is shown in Figure 14. It shows that batteries do not contribute that much to reducing the electricity bill during winter. During the summer, however, households on average find themselves in a situation where their electricity bill is negative, meaning suppliers need to pay them.

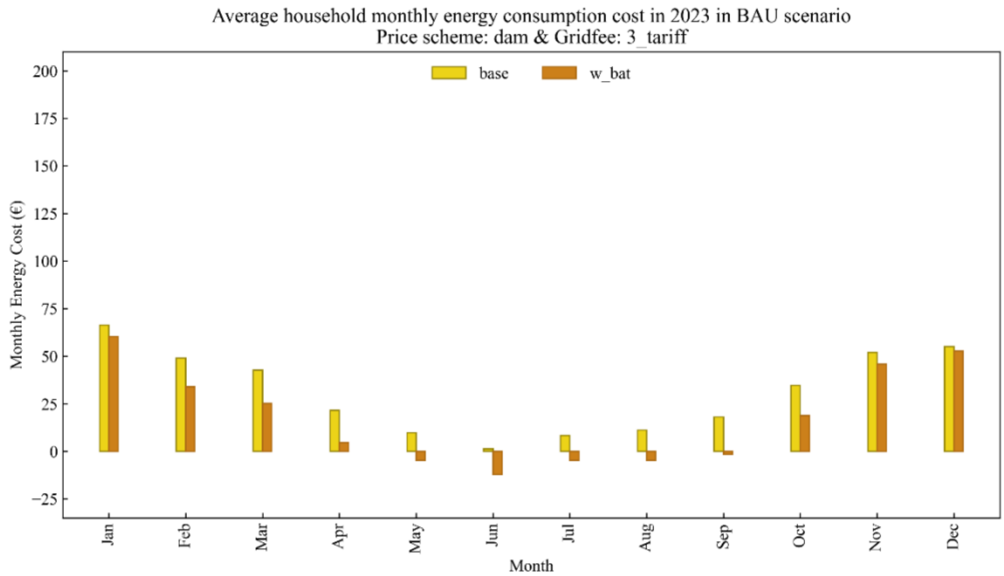
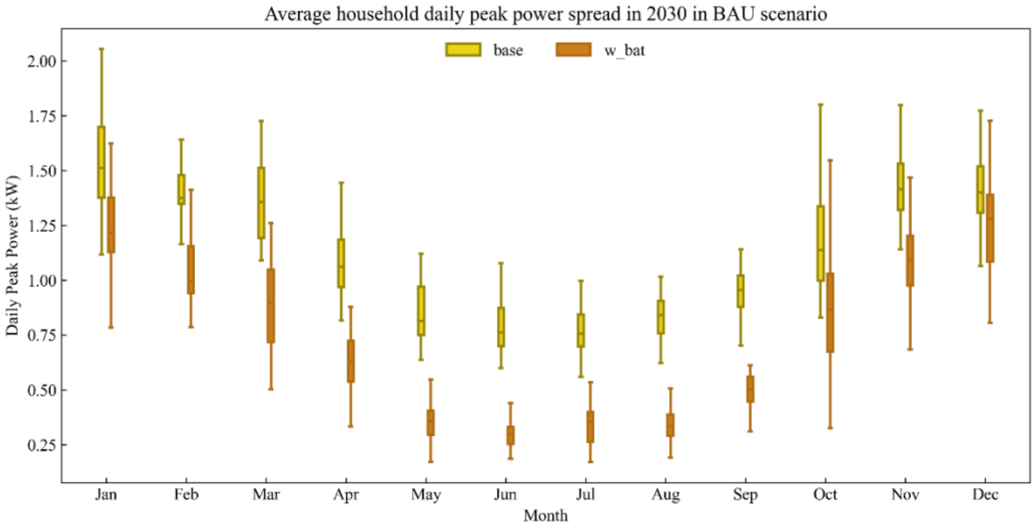


Figure 14 Average monthly electricity bill for day-ahead prices in 2023

V.4. Results for 2030

Figure 15 shows the average daily peak power spread across all households. For scenarios involving heat pumps, we ignored June, July, and August because during these months, heat pumps are mostly off. Adopting heat pumps results in an average increase of 0.53 kW in the base scenario's daily peak power. Thermal storage during the winter cannot help reducing daily peak power because, during this period, heat pumps are primarily used for space heating, so they are often on, and the amount of PV power available to charge the thermal storage is limited. Adding electrical and thermal storage mitigates the impact of heat pumps on daily peak power, especially during spring and fall, by effectively using PV generation and increasing the self-consumption of households. Batteries and thermal storage could decrease daily peak power on average by 22.65% compared to scenario 2.



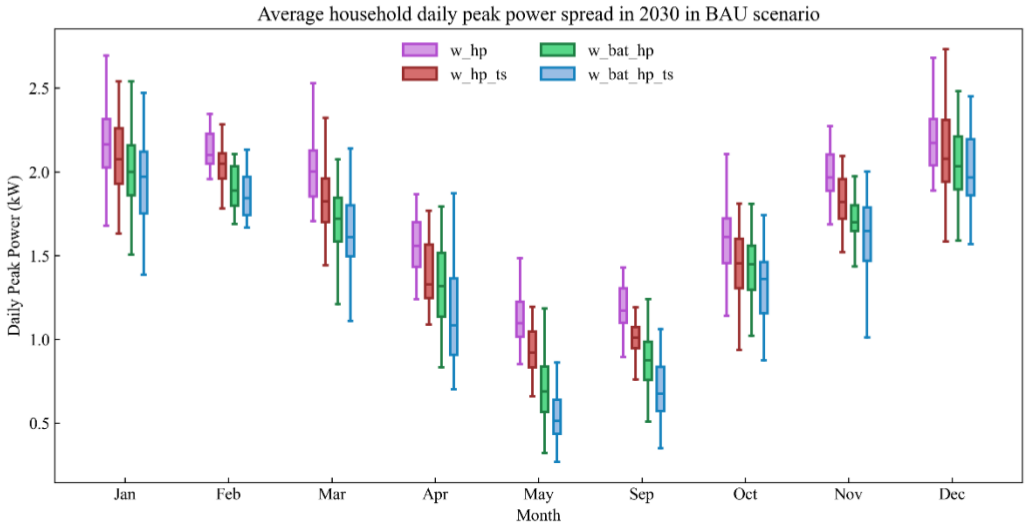


Figure 15 Average household daily peak power spread in 2030

Figure 16 demonstrates the average offtake energy profile across all simulated households in 2030. The average profiles show that heat pumps cause a spike in household energy consumption in the evening and at night, while slightly changing energy consumption during the day, making them a perfect complement to electrical and thermal storage.

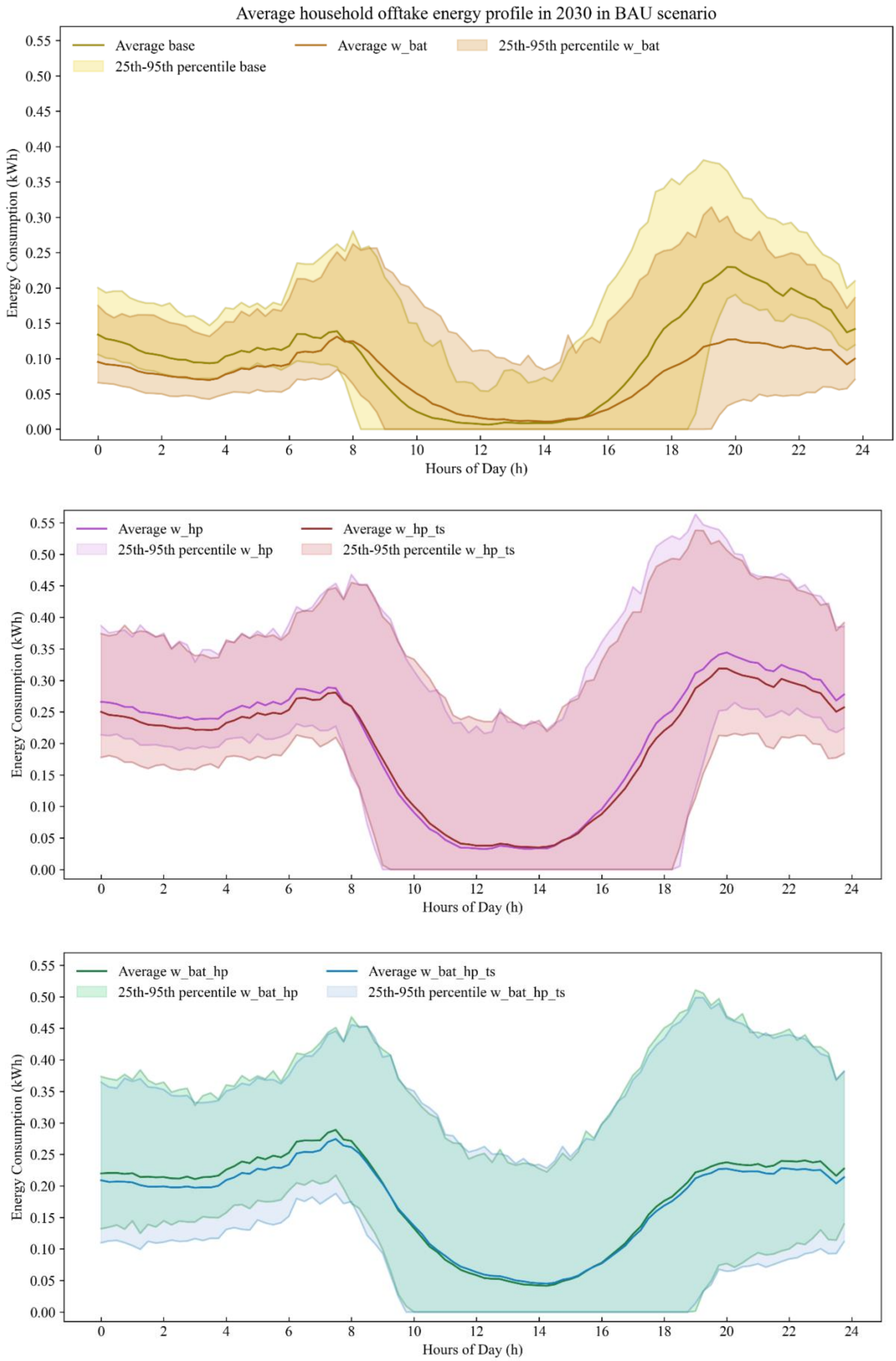


Figure 16 Average household offtake energy profile in 2030

An overview of the average annual electricity bill across all households in 2030 is tabulated in Table 3. Electrical and thermal storage lead to an average reduction of 189.13€ in the annual electricity bill when heat pumps are used. By comparing the average electricity bill in Scenarios 2, 3, and 4, we can conclude that the majority of the reduction in the annual electricity bill is due to batteries. The main reason is that the electrical output of the batteries used in this study is higher than that of the thermal storage: the smallest battery in this study has an output of 3 kW, while the thermal storage provides about 1.25 kW.

Table 3 Overview of the average annual electricity bill in 2030

DSO	Supplier	Base (€)	S1 (€)	S2 (€)	S3 (€)	S4 (€)	S5 (€)
Single-hourly tariff - ORES	Single-hourly tariff	495.61	323.03	1105.74	1050.64	936.75	905.13
	Day-ahead price	551.76	361.91	1168.90	1107.77	979.70	944.79
Bi-hourly tariff - ORES	Bi-hourly tariff	454.52	297.64	1003.19	958.50	850.98	825.67
	Day-ahead price	496.89	325.17	1052.37	1001.27	882.30	853.83
3-level tariff - ORES	3-level tariff tariff	495.93	310.55	1041.54	991.13	855.62	829.77
	Day-ahead price	522.77	331.23	1074.36	1019.91	880.53	852.29
Capacity tariff - Fluvius	Single-hourly tariff	331.54	213.46	751.34	717.86	643.97	623.99
	Day-ahead price	388.55	253.17	815.34	775.72	687.70	664.31

Figure 17 shows the average monthly electricity bill across all households. It reveals that storage has a minimal impact on reducing the electricity bill during winter. This highlights the fact that BAU control logics cannot efficiently leverage flexible assets because these logics are solely based on PV generation, which is low during winter.

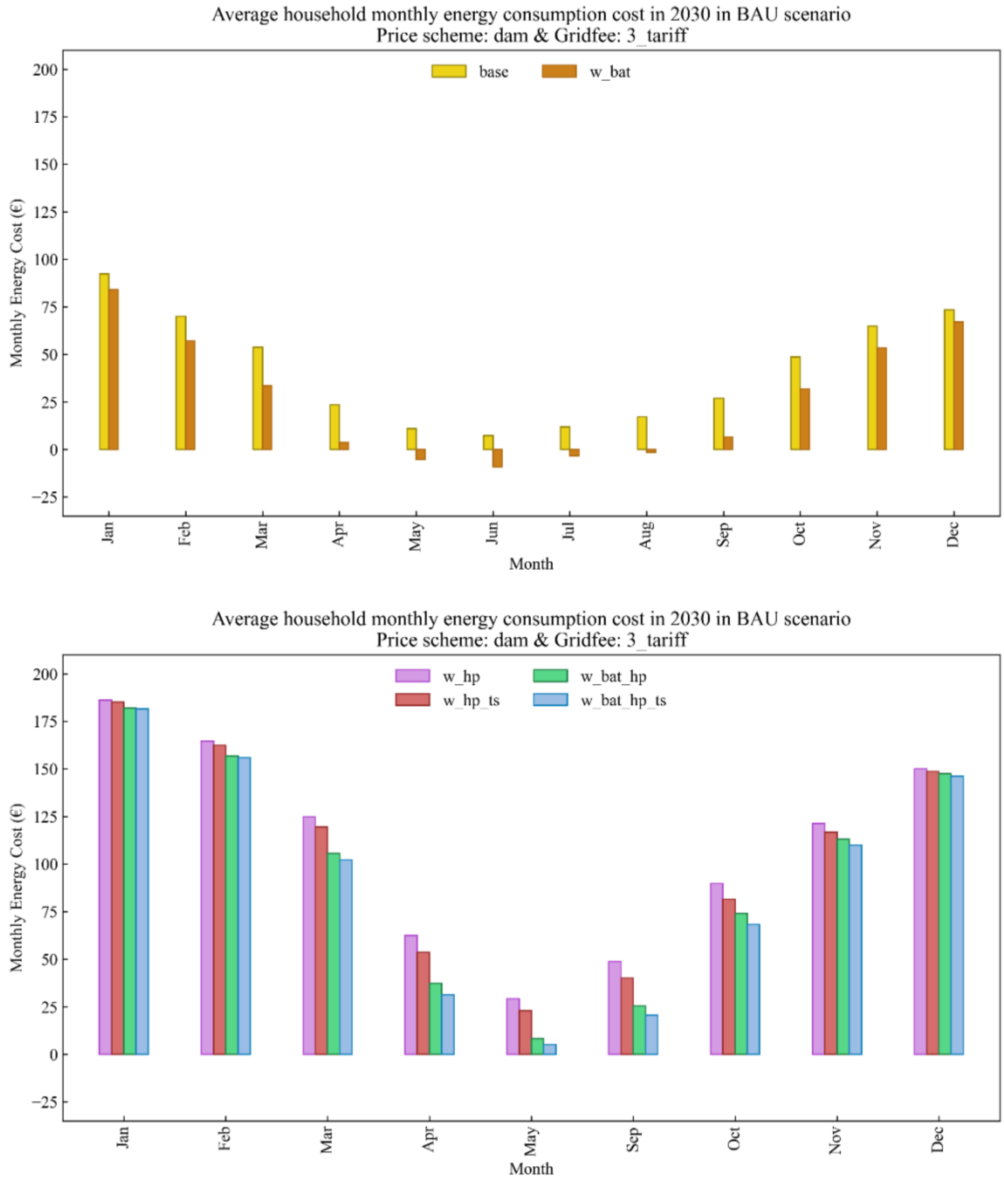


Figure 17 Average monthly electricity bill for day-ahead prices in 2030

V.5. Conclusion and Next Steps

Considering the evolution of the grid by 2030, the widespread adoption of heat pumps will significantly increase daily peak power and household electricity consumption. The results showed that integrating heat pumps with storage moderates their effects. However, BAU control logics for flexible assets are not the most suitable, as they rely solely on PV generation. Therefore, they cannot be effective in winter when PV generation is low. Although users will incur the highest electricity bills with 3-level tariffs and dynamic pricing, these schemes have the most potential to reduce bills when using smart controllers for flexible assets.

The next step is to develop smart controllers for heat pumps and storage to fully unlock their flexibility potential. These controllers can use inputs such as PV generation, electricity prices and other (flex) market incentives, and electricity consumption to manage flexible assets and minimize their electricity cost.

VI. References and Internet Links

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[4] Elia, “Adequacy & flexibility study for Belgium (2024-2034),” 2024.