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Heat Pump Flexibility in Day-Ahead Markets: A Case Study of the Losone Distribution Grid

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Summary

In this report, we quantify the potential profit that a hypothetical utility in the town of Losone could obtain by offering the flexibility of residential heat pumps in its distribution grid to the Swiss day-ahead electricity auction. This work serves as a benefit assessment of the flexibility bidding method proposed in Deliverable D2.4.3 and provides a link between WP1 and WP2. While WP1 evaluates the system-wide benefits of heat-pump flexibility using central-planner economic dispatch models, the present report adopts an operational perspective: we discuss how such flexibility can be exposed to the day-ahead dispatch on a daily basis and what economic value this creates for a local utility.

The first part of the report is methodological and outlines how aggregators of decentralised flexible resources (e.g., utilities) can communicate flexibility to the day-ahead auction via the bid formats offered by the Swiss nominated market operator, EPEX SPOT SE. The second part presents a detailed case study of the Losone distribution grid under varying heat-pump penetration levels and demonstrates how bidding flexibility in the day-ahead auction enables efficient shifting of heat demand toward periods of high renewable inflow and low market prices.

Key Results:

- In 2024, Swiss companies made 99% less use of “flexibility bids” in the day-ahead auction compared to neighbouring countries such as Germany and France. Such bids allow DSOs to reduce electricity procurement costs by shifting consumption to off-peak hours.
- In our 2023-2024 case study of the Losone DSO, applying flexibility bids for heat pumps would have reduced electricity procurement costs by 12.5%, corresponding to annual savings of approximately 75 CHF per heat pump. These savings result from shifting consumption to low-price hours through flexibility bidding.

Recommendations for Stakeholders:

- Swiss companies should begin to bid their demand-side flexibility in the day-ahead and intraday auctions, following the example set by several neighbouring European countries.
- The Swiss-nominated electricity market operator (EPEX SPOT) already provides a market design that enables participation by flexibility aggregators. What remains is for Swiss companies to actively make use of this existing framework, as their European counterparts already do.

1 Introduction

Flexibility at day-ahead and intraday timescales. Flexibility is needed on different timescales to balance demand and supply (Bardow et al. 2023). On day-ahead and intraday time scales, shiftable loads can provide flexibility by aligning consumption with available renewable production. Efficient coordination requires that flexibility providers participate in these markets, as day-ahead and intraday prices signal expected system needs, indicating when energy is scarce or abundant. For instance, low market prices indicate that RES production is high, whereas high prices suggest that fuel-based generators with higher marginal costs are needed to cover the system demand.

Flexibility aggregation in markets. The electrification of the heating and transportation sectors is introducing large amounts of inherently flexible demand into the energy system. In the future, heat pumps (HPs) and electric vehicles (EVs), are expected to account for a significant share of the total electricity demand, making it crucial that their flexibility is utilized in a system-friendly manner to avoid RES curtailment and facilitate the further integration of RES. However, these resources are numerous and small-scale, making it impractical to participate directly in the market. To unlock their flexibility potential, they must be aggregated and actively participate in power markets. We study participation in the Swiss day-ahead auction to estimate the profits gained from offering flexibility. In addition, intraday and balancing markets offer additional revenue streams; however, these markets are relatively small compared to the day-ahead auction, and there is a risk that they will saturate quickly with increasing investments in batteries.

Direct load control. While these resources help decarbonize the energy system, their additional load can lead to network congestion, especially in distribution grids (Bouloumpasis et al. 2019). Many Swiss distribution system operators (DSOs) have been proactive in anticipating grid congestion by offering direct load control (DLC) contracts for flexible loads such as EVs and HPs to avoid additional demand during highly congested periods (Mellot et al. 2025). These contracts typically allow the DSO to interrupt consumption during certain hours but not to actively increase load when market prices are low. As a result, the current use of flexibility primarily supports grid-friendly operation without yet contributing to broader system-level benefits. To assess the benefits of load shifting in response to day-ahead price signals, we assume that DSOs are allowed to control the heat pumps in a manner that maintains a stable temperature within the building.

Building thermal inertia. HPs can provide valuable short-term flexibility by leveraging the buildings thermal inertia to shift consumption from periods of high demand and prices to periods of lower demand and prices. By 2050, the number of installed HPs in Switzerland is expected to rise from the current 0.3 million to 1.5 million (Swiss Federal Office of Energy 2020). With an anticipated electricity demand of 17.9 TWh for residential and industrial HPs, this would represent a large share of the total electricity consumption (Nolzen et al. 2025).

Flexibility participation in auctions. In this work, we present a hands-on approach for utilities to aggregate small-scale, decentralized resources and offer their flexibility in day-ahead and intraday auctions. By applying the proposed approach to a realistic case study with HPs in the municipality of Losone, we evaluate the performance of the aggregation approach and the implications on cost savings and HP operation. Taking the perspective of a DSO that directly controls HPs, we quantify the monetary benefits of load shifting while ensuring that grid constraints are met.

Cost of participation. The primary cost associated with participation in the day-ahead market is the investment in heat pumps equipped with a smart-grid label, which enables external control. Currently, the price premium for a smart-grid-ready heat pump compared to a conventional model is estimated to be in the range of CHF 300–1,500. Based on Swiss day-ahead electricity price data from 2023–2024, our case study suggests that approximately CHF 75 per year could be saved through load shifting in the day-ahead market. This implies an amortisation period of roughly 5 to 20 years for the additional investment in a smart-grid-ready heat

pump.

However, the objective of this study is not to provide a detailed business case for investing in smart-grid heat pumps. The figures presented are illustrative rather than robust and do not account for future electricity price developments or technology cost trends. Instead, the main purpose of this study is to demonstrate, through a detailed case study, how aggregators can offer heat-pump flexibility in the Swiss day-ahead auction and to assess whether the current auction design enables efficient participation.

Positioning within PATHFNDR. This work is part of WP2 (district/city scale) and builds upon findings from the previous PATHFNDR deliverables D2.2.2 (Quantification of building flexibility), D2.3.2a (Flexibility-aware distribution network planning), D1.2.1 (Swiss heating sector) and D2.4.3 (Participation in electricity auctions).

2 Background

As dispatchable fossil-fuel-based generators are gradually replaced by variable renewable energy sources (RES), coordinating supply and demand becomes increasingly more challenging. This makes demand-side flexibility crucial for maintaining the balance in the electric energy system, with power markets serving as the primary coordination mechanism (Cramton 2017). By matching supply offers from generators with demand bids from consumers, power markets determine the market-clearing price for each time interval. These prices serve as scarcity signals, guiding both generation and consumption toward system needs: flexible generators produce when prices are high, while flexible consumers shift demand to periods of low prices and abundant renewable energy supply (Hirth 2013).

The electrification of heating and transport introduces substantial flexible demand into the energy system. Load shifting of heat pumps (HPs) and electric vehicles (EVs) can alleviate temporal mismatches between supply and demand, supporting RES integration while reducing curtailment and dependence on costly storage solutions (Mellot et al. 2025). Yet, the flexibility of these small-scale resources remains largely unexploited, as they are typically operated individually and without optimization. To unlock this potential, aggregators must offer the aggregated flexibility of individual resources on the market (Plaum et al. 2022).

For this purpose, the aggregator needs to compute the aggregated flexibility of the individual resources. Mathematically, the flexibility of a single resource can be represented as a set in a multi-dimensional power space, encompassing all feasible operating states of the resource over a given time horizon while accounting for intertemporal constraints such as energy limits (Zhao et al. 2016). Aggregating multiple resources then amounts to computing the Minkowski sum of their individual feasible sets - an NP-hard problem that quickly becomes intractable for large populations and long time horizons (Tiwarly 2008). A growing body of literature addresses this problem by developing inner (Taha et al. 2024, Müller et al. 2015, Müller et al. 2019, Ozturk et al. 2024, Nazir et al. 2018) and outer (Barot and Taylor 2017, Zhao et al. 2017, Barot and Taylor 2016) approximation methods, with the goal of finding approaches that are both accurate and computationally tractable (Öztürk et al. 2022). However, these methods do not discuss how to use the aggregate feasible sets in markets, limiting their practical applicability in systems operation.

Market participation requires that bids are expressed in a format defined by the market operator. In European day-ahead and intraday auctions, market participants can choose between different bid formats, which allow them to express their willingness to buy or sell electricity, based on their preferences and constraints (Herrero et al. 2020). In recent years, exclusive groups of block bids (also known as XOR package bids) have been identified as a promising bid format, especially for those resources with significant flexibility (Herrero et al. 2020, Karasavvidis et al. 2024, Hübner and Hug 2024, Hübner and Hug 2025).

Traditionally, bids in power markets were submitted for different time periods separately (Cramton 2017). To account for intertemporal constraints, block bids were introduced, enabling agents to bid on entire power profiles spanning multiple periods (Herrero et al. 2020). By grouping several block bids into an exclusive group (EG), the market-clearing algorithm is constrained to accept at most one of these bids (NEMO Committee 2024). Thus, an EG allows an agent to communicate B possible schedules (power profiles) to the auctioneer while guaranteeing that at most one is activated. Fig. 1 illustrates the concept: a shiftable load conveys its flexibility as an exclusive group of three block bids. The auctioneer can then select the schedule that best aligns with renewable generation by matching it against sell offers from renewable sources.

The use of EGs in European day-ahead auctions is illustrated in Table 1, which reports the total number of submitted EGs and the median number of bids per EG for the bidding zones Austria (AT), Belgium (BE), France (FR), Germany-Luxembourg (DE/LX), Great Britain (GB), the Netherlands (NL), and Switzerland (CH) in 2024. The data provide three key insights:

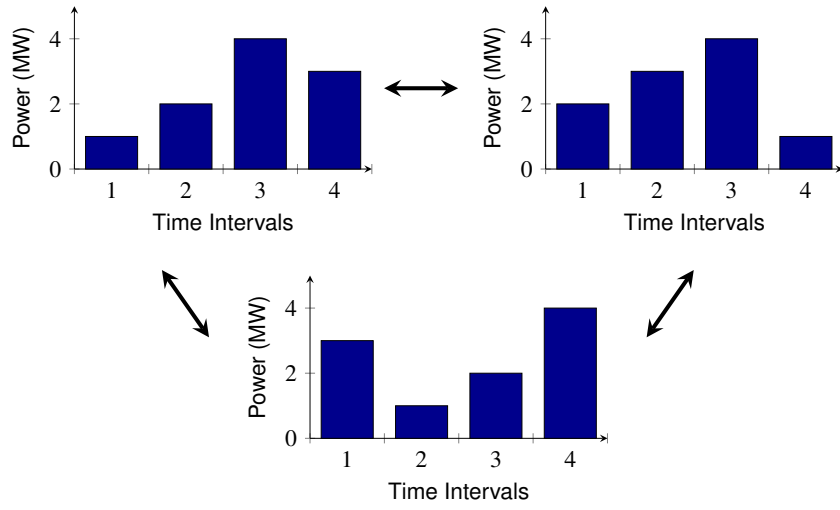


Figure 1: Exclusive group of three block bids.

- EGs are still used predominantly on the supply side, although some agents already employ them to express demand-side flexibility.
- Usage varies significantly across countries: while agents in some bidding zones rely heavily on EGs, in others they are scarcely applied.
- The maximum of 24 block bids per EG in the coupled European day-ahead auction (EPEX SPOT 2025, Nord Pool 2025) is often not fully used.

This indicates that, although market participants have already recognized the usefulness of EGs, their widespread adoption, particularly for communicating demand-side flexibility, remains largely unrealized. In particular, the frequent underuse of the 24-block limit suggests that less flexibility is being communicated than is likely available.

The limit of 24 block bids per EG is introduced by the market operator to ensure computational tractability of the market-clearing algorithm, shifting the task of pre-selecting suitable power profiles to market participants. This limitation introduces a *missing bids problem*, where participants are not able to bid on all of their possible power profiles (Goetzendorff et al. 2015). Recent studies have proposed bid selection algorithms to tackle this problem. However, existing studies focus exclusively on single assets such as hydropower plants (Aminabadi et al. 2025), flexible loads (Karasavvidis et al. 2024, Hübner and Hug 2025), thermal generators (Hübner and Hug 2025), or battery energy storage systems (Hübner and Hug 2025), rather than on aggregated portfolios.

Our work bridges this gap with respect to flexibility aggregation and market bidding by introducing a method directly applicable to European day-ahead and intraday auctions. Unlike the prevailing approaches in the flexibility aggregation literature, which aim to approximate the entire aggregated feasible region as closely

Table 1: Bid data of submitted exclusive groups in 2024.

Bidding zone	Demand-side EGs	Median buy bids/group	Supply-side EGs	Median sell bids/group
AT	52	1	1	2
BE	448	24	2,483	21
FR	2,259	17	11,260	22
DE/LX	2,101	13	12,589	15
GB	711	8	12,083	24
NL	298	12	5,923	24
CH	19	12	272	20

Note. The bid data were purchased from the power exchange EPEX SPOT.

as possible (Öztürk et al. 2022), we concentrate on identifying the subset that is economically relevant and conveying it to the market operator through EGs of block bids. This economically relevant region is identified by leveraging day-ahead and intraday price forecasts - readily available in practice (Lago et al. 2021) and widely used in the bidding literature to guide optimal bid construction (Hübner and Hug 2025).

Note that our method represents an application of the generic bidding framework introduced in (Hübner and Hug 2025) to the setting of flexibility aggregators. While that work provides the theoretical foundation, we focus on its concrete implementation for flexibility aggregators bidding in day-ahead and intraday auctions.

To evaluate the performance of our proposed *market-applicable flexibility aggregation method*, we apply it to a case study of a utility serving the Swiss town of Losone. In the considered setting, flexibility is provided by HPs distributed across the grid and is communicated to the Swiss day-ahead auction. We consider both the perspective of an *unbundled utility* (supplying customers without managing the grid) and an *integrated utility* (supplying customers while also managing the grid). This distinction reflects the Swiss integrated retail market, where local distribution system operators (DSOs) also act as electricity suppliers to households. By incorporating the distribution grid into our framework, we assess how aggregated flexibility can be harnessed not only in a system-friendly manner to reduce electricity procurement costs, but also in a grid-friendly manner to mitigate local network congestion.

The remainder of this paper is structured as follows. In Section 3, the methodology of the aggregation and bid selection algorithm is described. Section 4 focuses on the Losone case study, gives the mathematical formulation of the optimization model, and presents the results. Finally, Section 5 concludes the paper with a summary.

3 Methodology

We consider R flexible resources, indexed by $r \in \mathcal{R} = \{1, \dots, R\}$, each operating over T time periods, indexed by $t \in \mathcal{T} = \{1, \dots, T\}$. Each resource r has a feasible set $\mathcal{X}_r \subset \mathbb{R}^T$ representing all technically possible consumption (positive) or generation (negative) profiles, and a valuation function $v_r : \mathcal{X}_r \rightarrow \mathbb{R}$ representing the cost or benefit associated with a profile x_r .

The *aggregate feasible set* $\mathcal{X}_{\text{agg}}$ contains all power profiles that the aggregator can collectively implement. Mathematically, it corresponds to the Minkowski sum of the individual feasible sets:

$$\mathcal{X}_{\text{agg}} := \bigoplus_{r=1}^R \mathcal{X}_r = \left\{ x \in \mathbb{R}^T \mid x = \sum_{r=1}^R x_r, x_r \in \mathcal{X}_r \right\}.$$

Similarly, the aggregated valuation function representing cost/benefit is given by

$$v_{\text{agg}}(x) := \sum_{r=1}^R v_r(x_r).$$

In the following, we explain how an aggregator can bid approximations of $\mathcal{X}_{\text{agg}}$ and v_{agg} into the European day-ahead or intraday auctions via an exclusive group of block bids. We then outline how, based on the aggregator's bids, these auctions determine a dispatch $\bar{x}^* \in \mathcal{X}_{\text{agg}}$ for the aggregator through market clearing. Subsequently, we show how this aggregated dispatch can be disaggregated into individual dispatches $\bar{x}_r^*$ for each resource r . This procedure is summarized in Fig. 2 and explained in detail below.

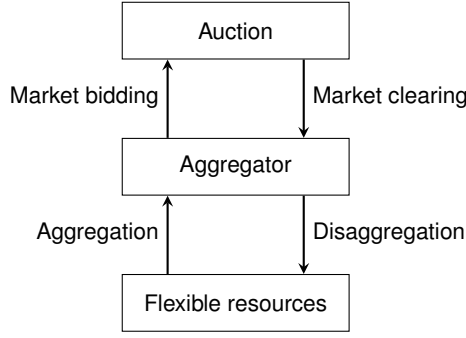


Figure 2: Aggregation steps between flexible resources, aggregator, and auction.

3.1 Market Bidding - Exclusive Groups of Block Bids

A block bid is given by (x_b, p_b) where $x_b = (x_{b1}, \dots, x_{bT})$ is a power profile and $p_b \in \mathbb{R}$ is the associated price. The acceptance rate of a bid is given by $\alpha_b \in [0, 1]$. The auctioneer can reject ($\alpha_b = 0$), fully accept ($\alpha_b = 1$) or partially accept ($\alpha_b \in (0, 1)$) a bid. Multiple block bids $b = 1, \dots, B$ can be submitted as part of an EG:

$$\mathcal{G} = \{(x_b, p_b) \mid b = 1, \dots, B\}. \quad (1a)$$

Submitting an EG ensures that at most one bid is fully accepted, or that multiple bids are partially accepted such that their total acceptance rate does not exceed one (constituting a convex combination):

$$\sum_{b=1}^B \alpha_b \leq 1. \quad (1b)$$

3.2 Aggregation - Determining B Block Bids

To determine B block bids (x_b, p_b) , we assume that a forecast of the electricity prices $\lambda = (\lambda_1, \dots, \lambda_T)$ is available, represented through $S = B$ price scenarios $\lambda_s \in \mathbb{R}^T$. For each scenario s and each resource r , we determine the optimal dispatch given prices λ_s by solving the profit-maximization problem

$$\bar{x}_{r,s} \in \arg \max_{x_r \in \mathcal{X}_r} [v_r(x_r) - \langle \lambda_s, x_r \rangle], \quad (2)$$

where $\langle \lambda_s, x_r \rangle = \sum_{t=1}^T \lambda_{s,t} x_{r,t}$ represents the forecasted revenue or cost, associated with schedule x_r under price scenario s . Consequently, the aggregated profile for scenario s is

$$\bar{x}_s = \sum_{r=1}^R \bar{x}_{r,s}, \quad p_s = \sum_{r=1}^R v_r(\bar{x}_{r,s}),$$

where $\bar{x}_s$ and p_s denote the aggregated power profile and the bid price under truthful bidding for scenario s , respectively. The resulting exclusive group $\mathcal{G}$ consisting of $B = S$ bids is given by

$$\mathcal{G} = \{(\bar{x}_s, p_s) \mid s = 1, \dots, S\}.$$

Note that aggregation is relatively simple, as just $R \cdot S$ small and easy-to-solve subproblems (2) need to be solved.

3.3 Market Clearing - Dispatch of the Aggregator

The algorithm EUPHEMIA used to clear the coupled European day-ahead and intraday auctions determines (approximately) a Walrasian equilibrium, where total supply matches total demand and no participant has an incentive to deviate from the outcome (Bichler et al. 2021, Hübner 2025). This means that only the optimal bid of each agent is accepted. That is, the market-clearing algorithm always accepts the most profitable bid $(\bar{x}^*, p^*)$ from $\mathcal{G} \cup (0, 0)$, or, if multiple bids yield the same profit, a combination of partially accepted bids:

$$(\bar{x}^*, p^*) \in \arg \max_{\alpha} \sum_{s \in \mathcal{G}} \alpha_s (p_s - \langle \tilde{\lambda}, x_s \rangle) \quad (3a)$$

$$\text{s.t. } 0 \leq \sum_{s \in \mathcal{G}} \alpha_s \leq 1, \quad (3b)$$

$$0 \leq \alpha_s \leq 1 \quad \forall s \in \mathcal{G}. \quad (3c)$$

3.4 Disaggregation - Dispatch of the Individual Resources

Once the auctioneer returns the accepted aggregated profile $\bar{x}^*$ from (3), disaggregation to individual resources is straightforward in our framework. For the accepted bid s^* that produced $\bar{x}^*$, we already have the optimal per-resource profiles $\{\bar{x}_{r,s^*}\}_{r=1}^R$ from the aggregation step. The aggregator can therefore instruct each resource r to follow its corresponding $\bar{x}_{r,s^*}$ without any additional optimization, ensuring that all technical constraints are satisfied. Similarly, if bids are only partially accepted, each resource r simply follows the corresponding convex combination of its individual schedules, which preserves feasibility since all $\bar{x}_{r,s}$ were optimal and feasible by construction.

3.5 Algorithm

The proposed aggregation and bid determination method is summarized in Algorithm 1.

Algorithm 1 Aggregation and bid determination

- 1: **Input:** S price scenarios $\{\lambda_s\}_{s=1}^S$, $\lambda_s \in \mathbb{R}^T$
 - 2: **for** $s = 1, \dots, S$ **do**
 - 3: **for** $r = 1, \dots, R$ **do**
 - 4: Solve $\bar{x}_{r,s} \leftarrow \arg \max_{x_r \in \mathcal{X}_r} [v_r(x_r) - \langle \lambda_s, x_r \rangle]$
 - 5: **end for**
 - 6: Aggregate: $\bar{x}_s \leftarrow \sum_{r=1}^R \bar{x}_{r,s}$, $p_s \leftarrow \sum_{r=1}^R v_r(\bar{x}_{r,s})$
 - 7: **end for**
 - 8: **Output:** Exclusive group $\mathcal{G} \leftarrow \{(\bar{x}_s, p_s)\}_{s=1}^S$
-

3.6 Example

As an illustrative example, consider the aggregate feasible set $\mathcal{X}_{\text{agg}}$ in Fig. 3 depicted by the black lines. Here, x_1 and x_2 denote the power production (negative values) and consumption (positive values) of the aggregated portfolio in time steps 1 and 2, respectively. The aggregated feasible set includes all possible power profiles of the aggregated resources within this two-hour period. Inner approximations (green lines) only cover part of the feasible set and may underestimate the available flexibility, while outer approximations (blue lines) cover

the full set but also include infeasible points. On the contrary, our method samples three power profiles (red dots) from $\mathcal{X}_{\text{agg}}$. The resulting EG then spans the red area as any convex combination of block bids in an EG can be accepted, see eq. (1).

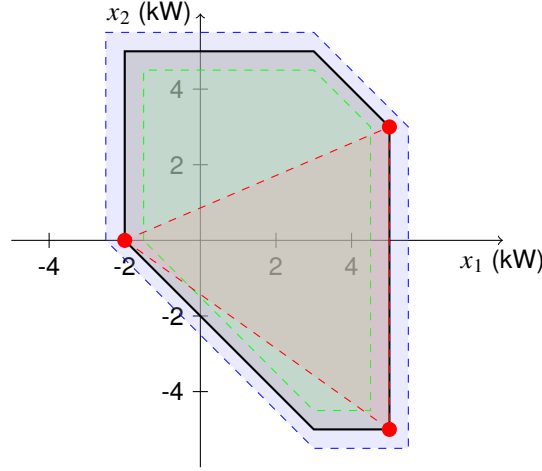


Figure 3: Approximation of the aggregate feasible set (black) using our method (red) and an inner (green) as well as outer approximation (blue).

3.7 Discussion

Ideally, an aggregator would submit the entire feasible set $\mathcal{X}_{\text{agg}}$ and valuation $v_{\text{agg}}(x)$ to the auction. If $\mathcal{X}_{\text{agg}}$ is a polyhedron, this could be achieved by bidding every vertex (corner point) as a block bid. In Figure 3, this corresponds to placing 6 block bids. The dispatch obtained through market clearing (3) would then be the aggregator's optimal dispatch.¹

In practice, however, the auctioneer imposes a bid limit B , requiring the aggregator to approximate $\mathcal{X}_{\text{agg}}$, as illustrated in Figure 3 assuming $B = 3$. The necessity of such a limit becomes apparent when considering that the optimization problem used to clear the coupled European day-ahead auction must determine an economic dispatch for the entire continent. By approximating $\mathcal{X}_{\text{agg}}$ using forecasts of the prices $\tilde{\lambda}$ - which correspond to the dual variables of the market's optimization problem - we can minimize approximation losses. See Hübner and Hug (2025) for further details on the theoretical background.

3.8 Network - The Case of an Integrated Utility

Note that so far we have assumed the resources $r = 1, \dots, R$ to be independent. This assumption holds for aggregators (*unbundled utilities*) operating in countries with liberalized retail markets, such as Germany or the UK. In contrast, in countries like Switzerland without a liberalized retail market, *integrated utilities* exist, which must both supply customers and manage the distribution grid. In this case, the individual feasible sets $\mathcal{X}_r$ of the resources are no longer independent, since the resources are coupled through network constraints, i.e., $(x_1, \dots, x_R) \in \mathcal{F}$. Therefore, for each scenario s , all resources are jointly optimized in a single optimization

¹Note that, by inspecting (3), it is clear that this optimal dispatch could also be obtained if the aggregator had prior knowledge of the market-clearing prices $\tilde{\lambda}$.

problem:

$$\begin{aligned} \bar{x}_S \in \arg \max \quad & \sum_{r=1}^R [v_r(x_r) - \langle \lambda_S, x_r \rangle] \\ \text{s.t.} \quad & x_r \in \mathcal{X}_r, \quad \forall r \in \mathcal{R}, \\ & (x_1, \dots, x_R) \in \mathcal{F}. \end{aligned}$$

This approach replaces the $R \cdot S$ independent optimization problems of the unbundled case with S optimal power flow (OPF) problems. For an explicit formulation of the network constraints $(x_1, \dots, x_R) \in \mathcal{F}$, we refer the reader to our case study in the distribution grid of Losone, Switzerland presented in Section 4.

4 Case Study

In this section, the proposed aggregation and bidding method is tested on a realistic case study. We focus on the load-shifting flexibility of HPs to optimally schedule their operation in the day-ahead market (DAM) with the objective of minimizing electricity procurement costs. Due to the thermal inertia of buildings, HPs can shift consumption from periods of high prices to periods of low prices with only minor effects on indoor temperature. This short-term flexibility potential of HPs has been widely studied, e.g., in (Marijanovic et al. 2022, Golmohamadi et al. 2021).

We apply our approach to both an unbundled and an integrated utility, representing an aggregator in a liberalized and monopoly-based retail market, respectively. We assume that the aggregator is allowed to directly control the HPs, but must ensure thermal comfort to end-users by keeping the indoor temperature within predefined temperature bounds.

All optimization models are formulated using JuMP in Julia version 1.11.5 and solved using Gurobi version 11.0.3 with default settings (Gurobi Optimization, LLC 2025) on a laptop with 32 GB RAM and an AMD Ryzen 7 PRO 6850U processor.

4.1 Data

The case study is calibrated on data from the municipality of Losone, Switzerland. The municipality comprises 2400 buildings, of which 350 are already equipped with HPs (approximately 15 %). From this initial configuration, we increase the HP share in increments of 15 % up to a maximum penetration of 60 %. For this, buildings with HPs are selected randomly, with the condition that once a building is equipped with an HP, it retains it in all subsequent scenarios with higher HP shares. This setup tests both the scalability of our method and shows to what extent the flexibility can be leveraged for peak shaving when the system demand increases, compared to an inflexible case. The number and capacity of HP installations for the different penetration levels are summarized in Table 2.

Table 2: heat pump installations in Losone.

Installed HPs	Total HP share	Installed HP electrical capacity
350	15 %	0.93 MW
720	30 %	2.00 MW
1080	45 %	3.00 MW
1440	60 %	4.00 MW

As the flexibility potential provided by HPs is mainly available in the heating season, we focus on the period from October 1, 2024, to March 31, 2025. The method is applied to the DAM with a time horizon of $T = 24$ hours and time intervals of $\Delta t = 1$ hour. The optimization model is solved separately for each day d and scenario s . For simplicity, these indices are omitted in the following formulation of the building and network model.

The input data for the case study are retrieved from the sources summarized in Table 3, whereas all fixed input parameters are shown in Table 4.

Table 3: Overview of data sources for the case study.

Input data	Data source
Outdoor temperatures	Open Meteo (Open-Meteo 2025)
Building parameters	Wen et al. (Wen et al. 2025)
Load	ENTSO-E transparency platform (ENTSO-E 2025)
Market prices	ENTSO-E transparency platform (ENTSO-E 2025)
Photovoltaic (PV) production	Demand.ninja (Staffell and Pfenninger 2025)
Installed PV capacity	Swiss Federal Statistical Office (Swiss Federal Statistical Office 2024)
Network data	Oneto et al. (Oneto et al. 2025b,a)

Table 4: Overview of input parameters.

Parameter	Description	Value	Unit
Building			
COP	Coefficient of performance	4.0	-
T^{set}	Set-point temperature	20.0	°C
T^{min}	Minimum indoor temperature	19.0	°C
T^{max}	Maximum indoor temperature	21.0	°C
Network			
V^{min}	Voltage lower bound (pu)	0.97	-
V^{max}	Voltage upper bound (pu)	1.03	-
RAR	Reactive-to-active power ratio	0.05	-
Cost			
$VoLL$	Value of lost load	10,000	€/MW h

4.2 Building model

The load-shifting flexibility depends both on the technical constraints of the HPs and on the comfort requirements of the households involved. Therefore, the individual buildings are modeled as single-node resistance-capacitance (RC) equivalent circuits, as illustrated in Fig. 4. To quantify the value of flexibility, HPs are operated in either an inflexible or a flexible mode.

The temperature dynamics of each building are described by the following continuous energy balance:

$$C \cdot \frac{dT^{\text{in}}}{dt} = \dot{Q}^{\text{HP}} - \dot{Q}^{\text{loss}},$$

where C is the building's thermal capacitance, $\dot{Q}^{\text{HP}}$ the heat supplied by the HP, and $\dot{Q}^{\text{loss}}$ the thermal losses through the building envelope. With buildings indexed by $b \in \mathcal{B} = \{1, \dots, B\}$, where $\mathcal{B}^{\text{HP}} \subseteq \mathcal{B}$ denotes the

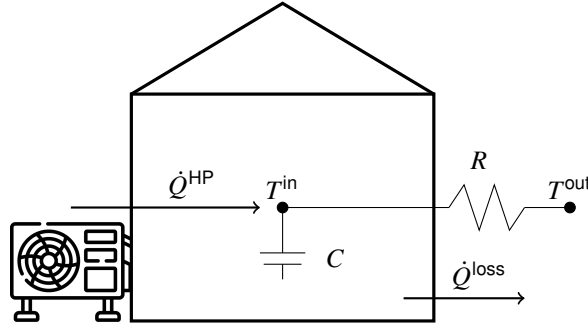


Figure 4: Single-node RC building model.

subset of buildings equipped with HPs, the discretized energy balance yields:

$$T_{b,t}^{\text{in}} = T_{b,t-1}^{\text{in}} + \frac{\Delta t}{C_b} \cdot \left(\text{COP} \cdot P_{b,t}^{\text{HP}} - \frac{T_{b,t}^{\text{in}} - T_t^{\text{out}}}{R_b} \right),$$

$$\forall b \in \mathcal{B}^{\text{HP}}, t \in \mathcal{T}, \quad (4)$$

where R_b denotes the thermal resistance, COP the coefficient of performance, $P_{b,t}^{\text{HP}}$ the electrical HP power, and $T_{b,t}^{\text{in}}$ and T_t^{out} the indoor and outdoor temperatures, respectively.

Inflexible HPs are assumed to maintain a constant set-point temperature T^{set} by compensating thermal losses. The baseline HP power $P_{b,t}^{\text{HP,base}}$ is given by:

$$P_{b,t}^{\text{base}} = \frac{T^{\text{set}} - T_t^{\text{out}}}{R_b \cdot \text{COP}}, \quad \forall b \in \mathcal{B}^{\text{HP}}, \forall t \in \mathcal{T}.$$

Flexible HPs are modeled as shiftable loads, whose daily energy consumption E_b^{base} must equal the one for the inflexible case², and the instantaneous HP power $P_{b,t}^{\text{HP}}$ is only constrained by the rated HP power $P_b^{\text{HP,rated}}$:

$$0 \leq P_{b,t}^{\text{HP}} \leq P_b^{\text{HP,rated}}, \quad \forall b \in \mathcal{B}^{\text{HP}}, \forall t \in \mathcal{T},$$

$$\sum_{t=1}^T P_{b,t}^{\text{base}} \cdot \Delta t = E_b^{\text{base}} = \sum_{t=1}^T P_{b,t}^{\text{HP}} \cdot \Delta t, \quad \forall b \in \mathcal{B}^{\text{HP}}.$$

Additionally, comfort is accounted for by imposing that the indoor temperature stays within predefined bounds:

$$T^{\text{min}} \leq T_{b,t}^{\text{in}} \leq T^{\text{max}}, \quad \forall b \in \mathcal{B}^{\text{HP}}, \forall t \in \mathcal{T},$$

$$T_{b,0}^{\text{in}} = T^{\text{set}}, \quad \forall b \in \mathcal{B}^{\text{HP}},$$

where T^{min} and T^{max} denote the minimum and maximum temperature, respectively. The initial temperature $T_{b,0}^{\text{in}}$ is fixed to the set-point temperature T^{set} .

4.3 Network model

In Switzerland's integrated retail market, the DSO is not only responsible for operating the distribution grid, but also supplying electricity to consumers. To represent this situation, the individual buildings are connected to the distribution grid of Losone. Since access to real-world electrical network data is restricted for privacy

²We enforce equal energy consumption for flexible and inflexible HPs to isolate the effect of shifting consumption to lower price periods. Without this constraint, flexible HPs would tend to operate closer to the lower temperature bound, thereby consuming less independently of the shifting effect.

and security reasons, we use synthetic medium-voltage (MV) and low-voltage (LV) grid instances sourced from Oneto et al. (2025b). These geo-referenced networks are derived from publicly available information and include node and edge data files with all necessary parameters (Oneto et al. 2025a). Fig. 5 illustrates the synthetic distribution network of Losone, with the MV network displayed in red and different LV networks distinguished by different colors.

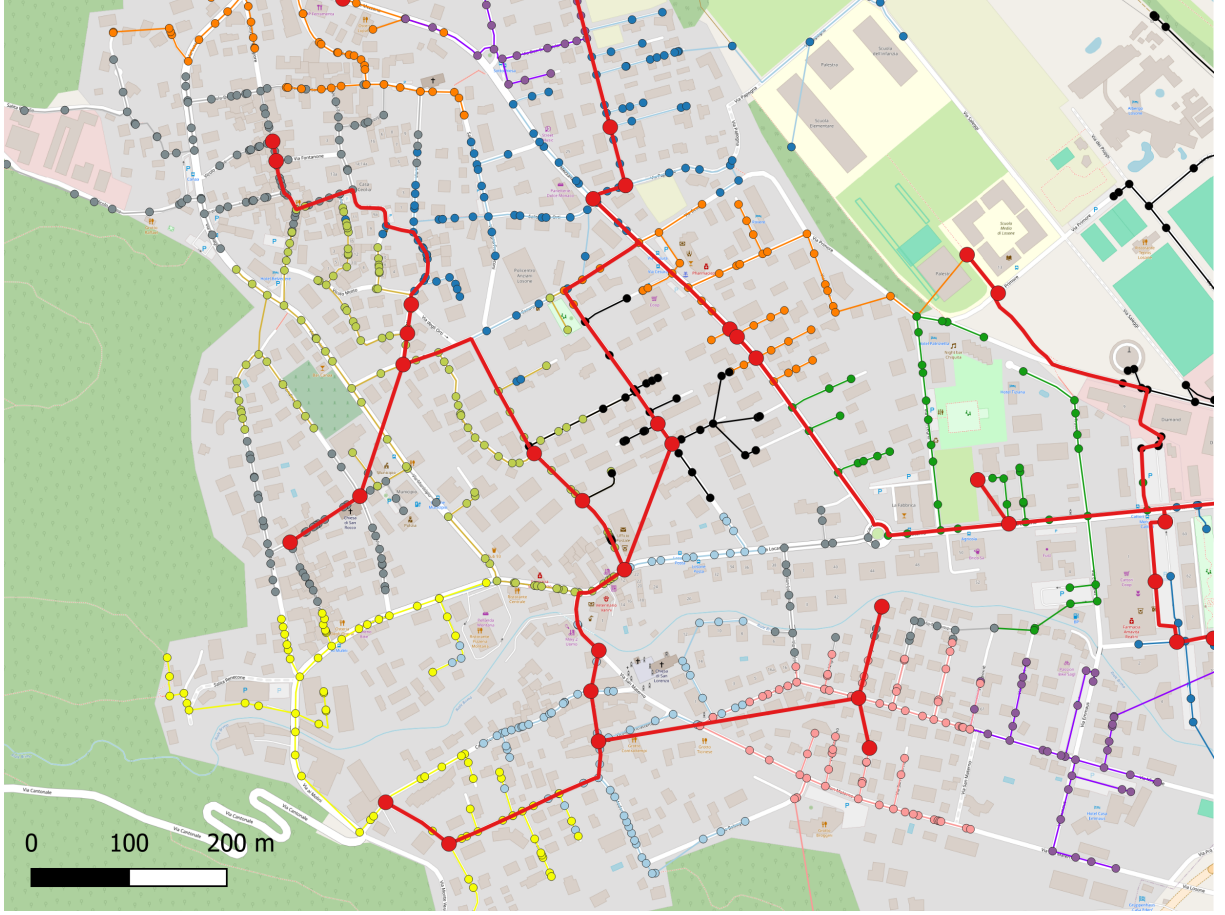


Figure 5: Representation of the Losone MV and LV distribution network.

Building allocation Individual buildings with their respective HP and PV capacities are allocated to network nodes. This allocation is determined by solving optimization problem (5), which minimizes the distance between building and node positions (X_b, Y_b) and (X_n, Y_n) , subject to assignment and capacity constraints. In this problem, each building $b \in \mathcal{B}$ is assigned to exactly one node $n \in \mathcal{N}$ through the binary variable $a_{n,b}$, while the node capacities P_n^{cap} obtained from the synthetic dataset limit the rated HP power $P_b^{\text{HP,rated}}$ and PV power $P_b^{\text{PV,rated}}$.

$$\begin{aligned}
 \min_{a_{n,b}} \quad & \sum_{n \in \mathcal{N}} \sum_{b \in \mathcal{B}} a_{n,b} \cdot \sqrt{(X_n - X_b)^2 + (Y_n - Y_b)^2} \\
 \text{s.t.} \quad & \sum_{n \in \mathcal{N}} a_{n,b} = 1, \quad \forall b \in \mathcal{B} \\
 & a_{n,b} \in \{0, 1\}, \quad \forall n \in \mathcal{N}, \forall b \in \mathcal{B} \\
 & \sum_{b \in \mathcal{B}} a_{n,b} \cdot P_b^{\text{HP,rated}} \leq P_n^{\text{cap}}, \quad \forall n \in \mathcal{N} \\
 & \sum_{b \in \mathcal{B}} a_{n,b} \cdot P_b^{\text{PV,rated}} \leq P_n^{\text{cap}}, \quad \forall n \in \mathcal{N}.
 \end{aligned} \tag{5}$$

After allocation, the aggregated HP and PV power at each node is obtained as the sum of the contributions

from all connected buildings:

$$P_{n,t}^{\text{HP}} = \sum_{b \in \mathcal{B}^{\text{HP}} \cap \mathcal{B}^n} P_{b,t}^{\text{HP}}, \quad \forall n \in \mathcal{N}, \forall t \in \mathcal{T},$$

$$P_{n,t}^{\text{PV}} = \sum_{b \in \mathcal{B}^{\text{PV}} \cap \mathcal{B}^n} P_{b,t}^{\text{PV}}, \quad \forall n \in \mathcal{N}, \forall t \in \mathcal{T}.$$

Network constraints When integrating the HPs into the distribution grid, their operation is constrained by the underlying network, governed by the power flow equations, and line, substations, and voltage limits must be satisfied. We assume radial distribution networks and use the linearized DistFlow formulation (Molzahn et al. 2019). We adopt a sending-end convention for line flows where power is positive when directed upstream (towards the substation) and negative when directed downstream (away from the substation). Each node has a unique ancestor, namely its adjacent node in the upstream direction, and a set of child nodes, i.e., its adjacent nodes in the downstream direction. Nodal injections are defined as positive for generation and negative for consumption.

The nodal power balances are described as follows:

$$P_{n,a,t} = \sum_{c \in \mathcal{C}_n} P_{c,n,t} + P_{n,t}^{\text{inj}}, \quad \forall n \in \mathcal{N}, \forall t \in \mathcal{T},$$

$$Q_{n,a,t} = \sum_{c \in \mathcal{C}_n} Q_{c,n,t} + Q_{n,t}^{\text{inj}}, \quad \forall n \in \mathcal{N}, \forall t \in \mathcal{T},$$

where $P_{n,a,t}$ and $Q_{n,a,t}$ denote the active and reactive power flows from node n to its ancestor a . The right-hand side consists of the sum of the flows $P_{c,n,t}, Q_{c,n,t}$ from all child nodes $c \in \mathcal{C}_n$ to node n , plus the net power injection $P_{n,t}^{\text{inj}}, Q_{n,t}^{\text{inj}}$ at node n .

Nodal injections are defined as follows:

$$P_{n,t}^{\text{inj}} = P_{n,t}^{\text{PV}} + P_{n,t}^{\text{LS}} - P_{n,t}^{\text{fix}} - P_{n,t}^{\text{HP}}, \quad \forall n \in \mathcal{N}, \forall t \in \mathcal{T},$$

$$Q_{n,t}^{\text{inj}} = \text{RAR} \cdot (-P_{n,t}^{\text{fix}} - P_{n,t}^{\text{HP}}), \quad \forall n \in \mathcal{N}, \forall t \in \mathcal{T},$$

where $P_{n,t}^{\text{fix}}$ denotes the inelastic demand, $P_{n,t}^{\text{LS}}$ the load shedding (penalized by VoLL). The parameter RAR is a fixed reactive-to-active power ratio.

Line and substation loading limits are defined by

$$P_{l,t}^2 + Q_{l,t}^2 \leq S_l^2, \quad \forall l \in \mathcal{L}, \forall t \in \mathcal{T},$$

$$P_{n,t}^2 + Q_{n,t}^2 \leq S_n^2, \quad \forall n \in \mathcal{N}^{\text{sub}} \subseteq \mathcal{N}, \forall t \in \mathcal{T},$$

where S_l and S_n are the apparent power ratings of line $l \in \mathcal{L}$ and substation node $n \in \mathcal{N}^{\text{sub}}$, respectively.

The voltage drop along each line $l = (i, j)$ connecting a sending node i and a receiving node j is given by

$$V_{i,t}^2 = V_{j,t}^2 - 2 \cdot (r_l \cdot P_{l,t} + x_l \cdot Q_{l,t}), \quad \forall l \in \mathcal{L}, \forall t \in \mathcal{T},$$

where r_l and x_l are the resistance and reactance of line l , respectively. Voltage magnitude constraints are imposed by

$$V^{\min} \leq V_{n,t} \leq V^{\max}, \quad \forall n \in \mathcal{N}, \forall t \in \mathcal{T},$$

$$V_{n,t} = V_n^{\text{nom}}, \quad \forall n \in \mathcal{N}^{\text{sub}}, \forall t \in \mathcal{T},$$

where $V^{\min}$ and $V^{\max}$ are the minimum and maximum voltage bounds, and V_n^{nom} the fixed nominal voltage at all substation nodes.

The synthetic dataset does not provide any time series for the nodes but only the connection capacity. To

obtain an hourly time series, we assume the same profile for each node. That is, we compute the Load Factor for Switzerland, denoted by SLF_t and defined as the ratio of the Swiss system load P_t^{CH} at time t to the annual peak load $P^{CH,max}$. The hourly electricity demand is obtained by scaling the capacity of the node by the SLF, i.e., $P_{n,t}^{dem} = P_n^{cap} \cdot SLF_t$. The load constraints are then described by

$$\begin{aligned} P_{n,t}^{fix} &= P_{n,t}^{dem} - P_{n,t}^{HP,base}, \quad \forall n \in \mathcal{N}, \forall t \in \mathcal{T}, \\ 0 &\leq P_{n,t}^{LS} \leq P_{n,t}^{fix}, \quad \forall n \in \mathcal{N}, \forall t \in \mathcal{T}. \end{aligned}$$

Hence, the inelastic demand is obtained by subtracting the baseline HP demand $P_{n,t}^{HP,base}$ from the total demand $P_{n,t}^{dem}$ and can be curtailed through load shedding.

The PV production is determined by

$$P_{b,t}^{PV} = P_b^{PV, rated} \cdot CF_t, \quad \forall b \in \mathcal{B}^{PV}, \forall t \in \mathcal{T},$$

where CF_t denotes the capacity factor at time t .

4.4 Bid determination

The bid determination consists of two major steps: the generation of different price scenarios and the determination of optimal power profiles based on these price scenarios. In our approach, aggregation reduces to a simple summation of the individual power profile vectors (cf. Algorithm 1).

Price Scenarios Electricity prices exhibit pronounced daily, weekly and yearly patterns, enabling accurate prediction of future prices (Weron 2014). For scenario generation, we use a two-step approach by first creating a point forecast and then applying a postprocessing method using the residuals from previous days to create the remaining scenarios. This approach is widely adopted in both literature and industry (Löhndorf et al. 2013) and has shown to perform competitively (Grothe et al. 2023).

In a first step, we use the open-source Python library *epftoolbox* to create a point forecast $y_{d,t}$ using the *LASSO Estimated Autoregressive* model (Lago et al. 2021). The model is trained on historical Swiss DAM price data from 2020–2025 with a four-year calibration and a one-year test period. In a second step, S price scenarios $\lambda_{d,t,S}$ are generated by incorporating residuals from the past $S - 1$ days as follows:

$$\begin{aligned} \lambda_{d,t,1} &= y_{d,t}, \\ \lambda_{d,t,2} &= y_{d,t} - (y_{d-1,t} - \lambda_{d-1,t}), \\ &\vdots \\ \lambda_{d,t,S} &= y_{d,t} - (y_{d-(S-1),t} - \lambda_{d-(S-1),t}), \end{aligned}$$

where the term $(y_{d-1,t} - \lambda_{d-1,t})$ represents the forecast residual from day $d - 1$ and hour t . The computation time for generating the price scenarios is negligible.

Unbundled Utility For determining optimal power profiles, we adapt the generic formulation of the optimization problem (2). Since all power profiles accumulate to the same daily energy consumption E^{base} and we assume that load shifting does not incur any cost, the valuation of all feasible power profiles $x_r \in \mathcal{X}_r$ are the same and proportional to the VoLL, given the utilities' obligation to supply the load:

$$v_r(x_r) = \text{VoLL} \cdot \Delta t \cdot \sum_{t \in \mathcal{T}} x_r, \quad \forall x_r \in \mathcal{X}_r.$$

Because this valuation is constant across all feasible profiles, it can be omitted from the optimization problem, and (2) simplifies to a cost-minimization problem, which for an unbundled utility is described by

$$\min \sum_{t \in \mathcal{T}} \Delta t \cdot \left(\lambda_t \cdot \sum_{b \in \mathcal{B}^{\text{HP}}} P_{b,t}^{\text{HP}} \right). \quad (6)$$

This optimization problem is solved repeatedly for all scenarios, and provides the power profiles for the block bids. In practice, we assume that the utility is willing to pay the maximum admissible bid price (MABP), currently at 4,000 €/MWh (EpexSpot 2024). The resulting submitted block bids $\bar{x}_s$ and the scenario-independent bid price p are then given by

$$\bar{x}_s = \sum_{b \in \mathcal{B}^{\text{HP}}} P_{b,s}^{\text{HP}}, \quad p = \text{MABP} \cdot \sum_{b \in \mathcal{B}^{\text{HP}}} E_b^{\text{base}}.$$

Integrated Utility For an integrated utility, HP operation is further restricted by the constraints described in the network model in Section 4.3. Therefore, the optimal dispatch problem extends to an OPF problem. As the share of HPs in the network increases (cf. Table 2), a point is reached where load shedding can no longer be avoided, since network reinforcements - which would occur in practice - are not modeled. Consequently, the objective function (7) must be augmented with a term that accounts for load shedding:

$$\min \sum_{t \in \mathcal{T}} \Delta t \cdot \left(\lambda_t \cdot P_t^{\text{PCC}} + \text{VoLL} \cdot \sum_{n \in \mathcal{N}} P_{n,t}^{\text{LS}} \right), \quad (7)$$

where P_t^{PCC} denotes the power exchange at the point of common coupling with the high voltage grid, and VoLL the value of lost load (or load shedding penalty). Since load shedding is highly penalized, flexibility is primarily leveraged for peak shaving, with the remaining flexibility used to react to price signals.

4.5 Benchmark - Aggregation Efficiency

We compare our aggregation method with the theoretical optimum that could be achieved if it were possible to bid the entire aggregate feasible set $\mathcal{X}_{\text{agg}}$. We define the aggregation efficiency η as the realized share of the theoretical maximum cost savings:

$$\eta = \frac{TC^{\text{inf}} - TC^{\text{cleared}}}{TC^{\text{inf}} - TC^{\text{opt}}},$$

where TC^{inf} are the total costs under inflexible operation, TC^{cleared} the total costs achieved by bidding an EG, and TC^{opt} the minimum achievable total costs if $\mathcal{X}_{\text{agg}}$ would have been submitted. The optimal cost TC^{opt} corresponds to the case of perfect foresight of market prices. Hence, it is obtained by solving the optimization model with the realized market-clearing price $\tilde{\lambda}$ for the unbundled and integrated utility cases, as given in (6) and (7), respectively. This definition captures how effectively the aggregation and bidding approach translates into economic performance.

4.6 Results

The performance of our aggregation approach is evaluated by two key performance indicators: the aggregation efficiency and the computation time. In particular, these indicators are analyzed with respect to the number of bids and the number of resources.

Aggregation Efficiency Fig. 6 shows the aggregation efficiency for different numbers of submitted bids at

a fixed 15 % HP share, with overlapping curves for the unbundled and integrated utilities. The case $B = 1$ corresponds to submitting only a single schedule with a single block bid instead of using EGs. By employing EGs, aggregation efficiency can be increased from 91 % to 98 %, converging closely towards an optimal bid. Since these results were achieved with publicly available price forecasting tools, they can be seen as a lower bound for market agents with access to more advanced forecasting methodologies. Our findings show that the aggregation efficiency increases monotonically with the number of submitted bids. Although the efficiency saturates, it remains advantageous to fully exploit the maximum allowed limit of 24 bids.

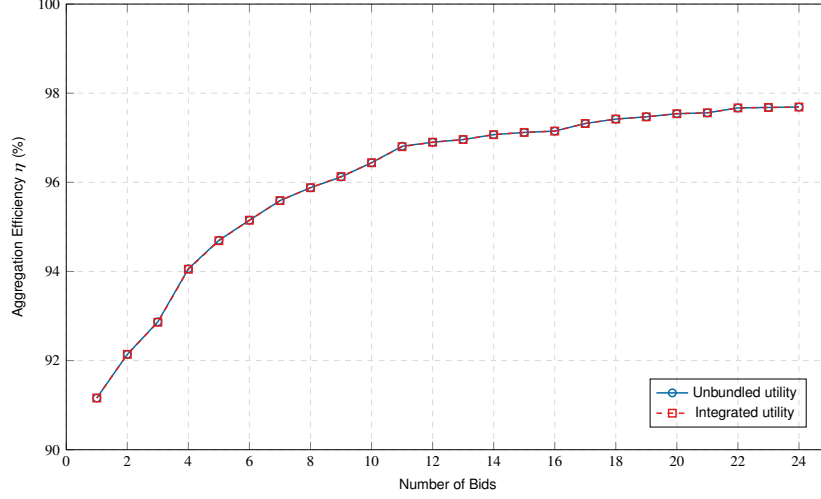


Figure 6: Aggregation efficiency for different numbers of submitted bids.

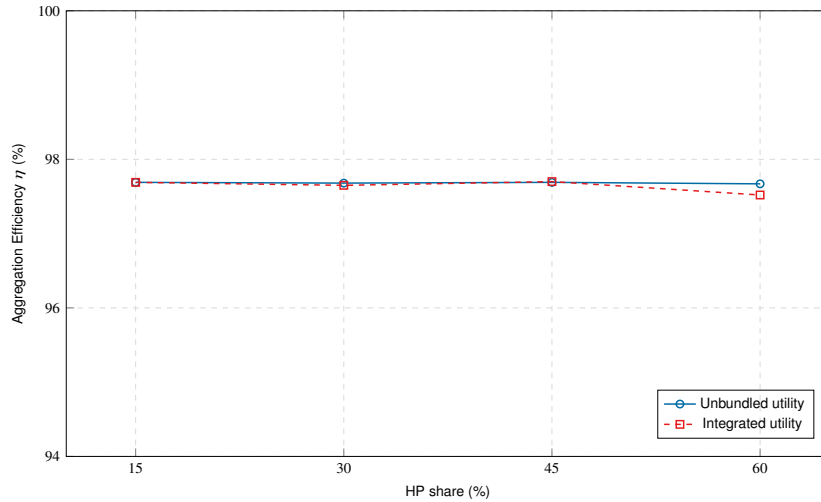


Figure 7: Aggregation efficiency for different HP shares.

Fig. 7 shows the aggregation efficiency for different numbers of resources, comparing the unbundled and integrated utility cases at a fixed bid number of 24. For the unbundled utility, the aggregation efficiency remains unaffected as the number of resources increases, highlighting that the proposed approach is scalable without efficiency loss. For the integrated utility, aggregation efficiency decreases slightly at higher HP shares due to arising grid congestion.

Computation time The cumulative computation time is illustrated for different numbers of bids at a fixed 45 % HP share in Fig. 8, and for different HP shares at a fixed number of 24 bids in Fig. 9, respectively.

For the unbundled utility, computation time is directly proportional to the number of bids and resources. For the integrated utility, computation time is proportional to the number of bids, but shows a polynomial increase with the number of resources. This difference is due to the fact that the unbundled case decomposes into $R \cdot S$ optimal dispatch problems (cf. Algorithm 1), while the integrated utility case requires solving S OPF problems

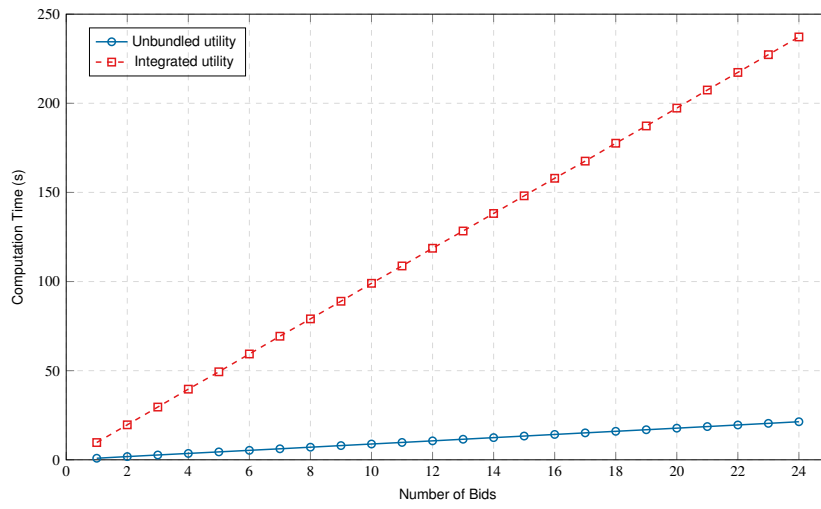


Figure 8: Computation time for different bid numbers.

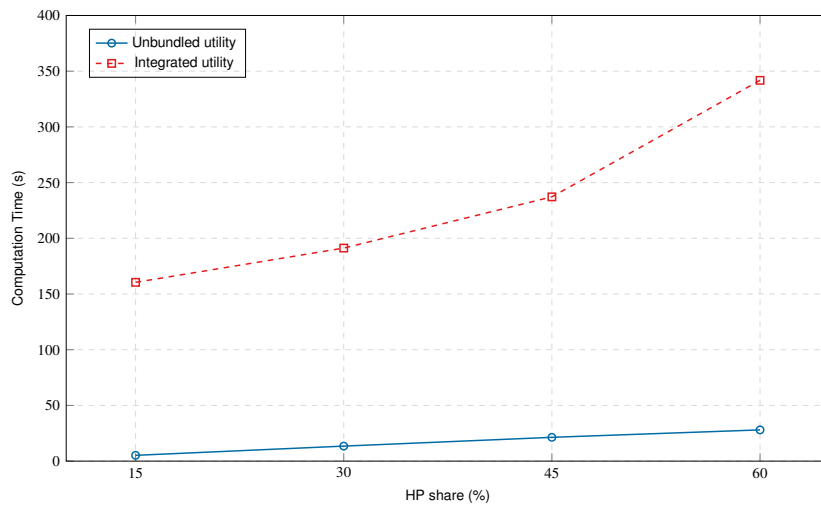


Figure 9: Computation time for different HP shares.

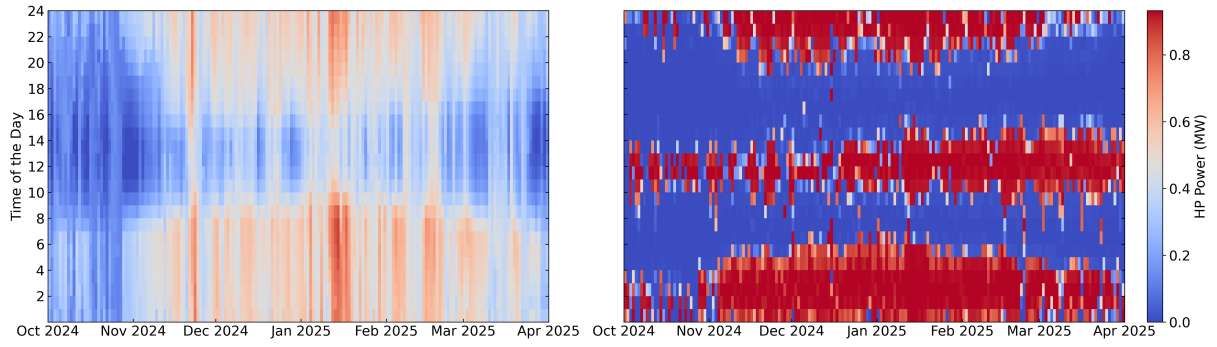


Figure 10: Comparison of consumption patterns for inflexible (left) and flexible (right) HPs.

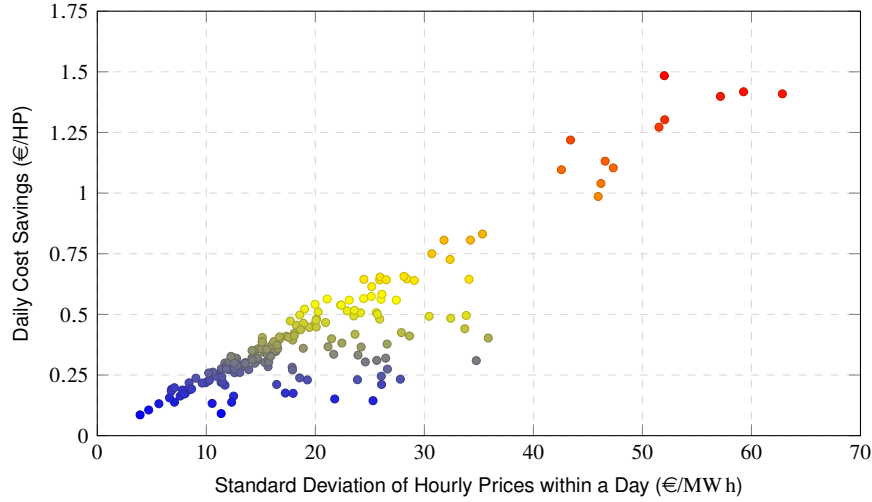


Figure 11: Scatter plot of daily cost savings and price volatility.

(cf. Section 3.8). In both cases, the proposed approach offers a computationally efficient method to determine bids within minutes.

Cost savings Taking advantage of the building inertia to respond to price signals alters the way in which HPs are operated. Fig. 10 illustrates the consumption profiles of inflexible and flexible HPs at a 15% HP share. The operation of inflexible HPs follows outdoor temperature patterns, with slightly higher consumption during nighttime due to lower temperatures. In contrast, flexible HPs adjust their operation in response to price signals from the DAM. As a result, consumption is primarily shifted toward low-cost periods during nighttime and midday, and away from high-cost periods in the morning and evening. This shows that their operation aligns with system needs by reducing demand during peak hours and increasing it during times of high generation and low demand.

Our results highlight that the daily cost savings are closely related to the price volatility throughout the day. This is illustrated in Fig. 11, where the relationship between daily cost savings and the standard deviation of hourly prices relative to the daily mean is shown for all days.

By taking advantage of volatile prices and occasional price dips, daily electricity costs can be reduced, leading to substantial overall savings. Over the considered time horizon, both the unbundled and integrated utility reduce electricity procurement costs by around 12.5% across all HP shares compared to the inflexible operation, corresponding to cost savings of around 80 €/HP. Table 5 summarizes the total electricity procurement costs under perfect price foresight for different HP shares and operating modes.

For low HP shares, there is no noticeable difference in HP costs between the unbundled and integrated utility, indicating that the distribution grid is not constraining HP operation. For higher HP shares, grid-aware flexibility

is prioritized, where load shifting is primarily used to perform peak shaving.

Table 5: Total HP costs for the different operating modes.

Operating mode	15 % HPs	30 % HPs	45 % HPs	60 % HPs
Inflexible	212,891 €	458,091 €	685,263 €	914,132 €
Unbundled	186,183 €	400,655 €	599,286 €	799,682 €
Integrated	186,183 €	400,883 €	599,706 €	803,781 €

5 Conclusion

We proposed a method that enables an aggregator to bid aggregated flexibility in European day-ahead and intraday electricity auctions. To demonstrate the approach, we applied it to both an unbundled and an integrated utility in the town of Losone, where flexibility is provided by heat pumps and offered in the Swiss day-ahead auction.

Our aggregation method offers the following advantages:

- *Technology-agnostic*: Compatible with all decentralized flexible resources (EVs, HPs, etc.).
- *Market-ready*: Already applicable in most European day-ahead and intraday auctions.
- *Scalable*: Computation time grows linearly with the number of resources when grid constraints are not considered.
- *Accurate*: Delivers high accuracy given reasonably accurate electricity price forecasts.

The main limitation of our approach is its dependence on price forecasts. While forecast accuracy declines with higher renewable penetration, even imperfect forecasts provide useful signals for flexibility aggregation.

From our study, we can derive the following recommendations:

- *Aggregators* should utilize EGs to convey decentralized flexibility to the system.
- *Nominated Electricity Market Operators (NEMOs)* who already offer EGs should increase the number of bids per group (e.g., from 24 to 100) to enable participants to express a larger share of their flexibility. NEMOs that are not yet supporting EGs should introduce them to facilitate the market integration of decentralized flexibility.

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