Flexible operation of residential heat pumps under dynamic electricity prices—A data-driven economic assessment

Jendrik Kasper[a,b], Mathias Hofmann[c], Janosch Balke[d], Stefan Elbel[e], Katharina Herkendell[f]

[a] *Technische Universität Berlin, Institute of Energy Engineering, Berlin, Germany*
[b] *Green Way Energy, Berlin, Germany*
[c] *Technische Universität Berlin, Chair of Energy Process Engineering and Conversion Technologies for Renewable Energies, Berlin, Germany, hofmann@iet.tu-berlin.de, CA*
[d] *Viessmann Climate Solutions / Carrier, Allendorf (Eder), Germany*
[e] *Technische Universität Berlin, Chair of Heat Transfer and Heat Conversion, Berlin, Germany*
[f] *Technische Universität Berlin, Chair of Energy Process Engineering and Conversion Technologies for Renewable Energies, Berlin, Germany*

Abstract:

This paper investigates the economic potential of flexible, price-driven operation of residential heat pumps using real measurement data from 2024. A data-based optimization model was developed in Pyomo to simulate various system configurations, considering building thermal inertia, heating systems (radiators and underfloor heating), buffer storage, and PV coupling. Hourly dynamic electricity prices were applied to identify cost-minimizing operating strategies. Results indicate that flexible operation enables significant load shifting and cost reductions of up to 30% in idealized scenarios, while realistic strategies yield savings between 5% and 20%. Building mass was identified as the dominant factor influencing flexibility. Buffer storage offered only marginal advantages, particularly for underfloor heating. PV coupling proved beneficial for self-consumption and grid independence. The findings demonstrate that price-based heat pump control can enhance household economics and provide a foundation for dynamic tariff models and demand-side flexibility in future energy systems.

Keywords:

Energy system analysis, Heat pumps, Optimization, Python

1. Introduction

Heat pumps are widely regarded as a key technology for the decarbonization of the residential heating sector and play a central role in achieving climate neutrality targets in Europe and Germany in particular. In recent years, their market penetration has increased significantly, especially in new residential buildings, where heat pumps have become the dominant heating technology [1, 2]. This development is driven by rising prices for fossil fuels, regulatory measures targeting greenhouse gas emissions in the building sector, and the increasing availability of renewable electricity generation [3].

Despite their high theoretical efficiency, the adoption of heat pumps in existing residential buildings remains constrained by economic concerns. Surveys among homeowners consistently identify high and volatile electricity prices as one of the main barriers to investment in heat pump systems [4]. Since the operating costs of electrically driven heating systems are directly linked to electricity prices, households face uncertainty regarding long-term affordability, particularly in liberalized electricity markets with increasing price volatility [5]. Improving the economic performance of heat pumps under real market conditions is therefore a key factor for their broader acceptance.

At the same time, the transformation of the electricity system towards a high share of variable renewable energy sources, such as wind and photovoltaics (PV), increases the need for flexibility on the demand side [6]. Flexible electricity consumers can help balance generation and demand, reduce curtailment of renewable energy, and mitigate stress on electricity grids [7]. Residential heat pumps represent a promising source of demand-side flexibility, as their electricity consumption can be shifted in time by exploiting the thermal inertia of buildings and heating systems, while maintaining acceptable indoor comfort levels [8].

Several studies have demonstrated that flexible or price-driven operation of heat pumps can generate economic benefits for households and contribute to system-level efficiency [9–11]. However, many existing analyses rely on simplified building models, synthetic demand profiles, or idealized control strategies that neglect practical constraints such as thermal comfort bands, cycling behavior of compressors, or realistic system sizing. Moreover, the achievable savings depend strongly on building characteristics, heating system types (e.g. radiators versus underfloor heating), and the integration of additional system components such as thermal buffer storage, photovoltaic systems, or battery storage [12, 13]. The interaction of these factors is often insufficiently addressed in a unified modeling framework.

Another limitation of the current literature is the frequent use of generic input data or typical meteorological years, which may not adequately capture real operational conditions and actual electricity price dynamics. Analyses based on real measurement data are still relatively scarce, despite their importance for assessing realistic savings potentials and operational feasibility [14]. In particular, recent years have shown increased electricity price volatility, making it necessary to reassess flexibility potentials under current market conditions [15].

1.1. Aim of work, paper structure, and data availability

This paper addresses these gaps by quantifying the economic potential of flexible, price-driven operation of residential heat pumps using real operational data from 2024. A data-driven optimization model is developed to represent different building thermal masses, heating system configurations, and optional components such as thermal buffer storage, PV systems, and battery storage. Hourly dynamic electricity prices are applied to determine cost-optimal operating strategies under explicit comfort and technical constraints. Both theoretical maximum savings and more realistic operating strategies, including limitations on excessive cycling, are analyzed.

The main contributions of this work are threefold. First, it provides a quantitative assessment of cost savings achievable through flexible heat pump operation under real electricity market conditions. Second, it identifies the key system and building parameters that govern flexibility and economic performance, with a particular focus on building thermal inertia. Third, it evaluates the additional value of thermal and electrical storage within integrated residential energy systems.

The remainder of this paper is structured as follows. Section 2 describes the modeling approach, optimization framework, and investigated scenarios. Section 3 presents the data sources and parameter assumptions. Section 4 discusses the results of the economic and sensitivity analyses. Section 5 provides a critical discussion of the findings in the context of existing literature. Finally, Section 6 concludes the paper and outlines directions for future research.

Data used in this study are real measurement information from a residential heat pump manufacturer. An anonymous and normalized dataset and the source code is available on request.

2. Methodology, system design, and parameters

2.1. System modeling

The system under investigation represents a single-family residential building equipped with a heat pump-based heating system. The building thermal behavior is described by a single-zone model with an effective heat capacity c_{eff}, which captures the thermal inertia of the heated interior while maintaining computational tractability for annual simulations. Under the assumption of hourly stationarity, the indoor air temperature θ_t evolves according to the energy balance

$$\theta_t = \theta_{t-1} + \frac{\dot{Q}_{\mathrm{HP}}(t) - \dot{Q}_{\mathrm{demand}}(t)}{c_{\mathrm{eff}}}, \tag{1}$$

where $\dot{Q}_{\mathrm{HP}}(t)$ denotes the heat delivered by the heat pump and $\dot{Q}_{\mathrm{demand}}(t)$ the measured hourly heat demand. When supply matches demand exactly, the indoor temperature remains constant; deviations cause temperature drift bounded by a seasonal comfort band.

To represent buildings of differing construction quality, three thermal mass categories—light, medium, and heavy—are parameterized following DIN EN ISO 52016-1, assuming a floor area of 150 m^2. The effective heat capacity per zone is derived from the area-specific heat capacity C_{areal} and the floor area A_{eff}:

$$c_{\mathrm{eff}} = \frac{c_{\mathrm{areal}} \cdot A_{\mathrm{eff}}}{3.6 \times 10^6} \quad [\mathrm{kWh/K}], \tag{2}$$

yielding values of 4.58, 6.88, and 10.83 kWh/K for light, medium, and heavy buildings, respectively. For systems with underfloor heating (UFH), screed mass provides additional thermal storage capacity. This is accounted for by applying a construction-class-specific scaling factor f_{UFH}:

$$c_{\mathrm{eff}} = c_{\mathrm{eff,base}} \cdot f_{\mathrm{UFH}}, \tag{3}$$

with $f_{\text{UFH}} \in \{1.6, 2.0, 2.2\}$ for light, medium, and heavy buildings, respectively. For radiator systems, $f_{\text{UFH}} = 1$ applies. Two heat pump types are included: air-to-water (ASHP) and brine-to-water (GSHP) units.

The heat pump is modeled using a data-driven coefficient of performance *COP*, derived directly from real operational measurements:

$$COP_t = \frac{\dot{Q}_t}{P_t}, \tag{4}$$

where $\dot{Q}_t$ is the measured thermal output and P_t the measured electrical power consumption at time step t. This formulation implicitly captures the effects of ambient temperature, supply temperature level, and part-load behavior without requiring an explicit thermodynamic model. Operational bounds constrain the heat pump to deliver between 20% and 100% of its observed peak thermal output during heating hours, representing the physical modulation range of the compressor:

$$\frac{0.2 \cdot P_{\max}}{COP_t} \leq \dot{Q}_{\text{HP}}(t) \leq \frac{P_{\max}}{COP_t}, \tag{5}$$

where $P_{\max}$ denotes the maximum electrical power observed in the measurement dataset over the full year.

An optional thermal buffer storage is modeled as a water tank with a volume of 400 L, a usable temperature lift of 5 K, a resulting storage capacity *CAP* of approximately 2.27 kWh, and a proportional heat loss coefficient k_{loss}. Its state of charge evolves as:

$$SOC_t = SOC_{t-1} + \dot{Q}_{\text{HP}\rightarrow\text{Tank}}(t) - \dot{Q}_{\text{Tank}\rightarrow\text{SH}}(t) - \dot{Q}_{\text{loss}}(t), \tag{6}$$

where heat losses are proportional to the current charge level:

$$Q_{\text{loss}}(t) = k_{\text{loss}} \cdot \frac{SOC_{t-1}}{CAP}. \tag{7}$$

Discharge is constrained by the energy available at the previous time step, i.e., $Q_{\text{Tank}\rightarrow\text{SH}}(t) \leq SOC_{t-1}$. Parameters are derived from manufacturer datasheets.

For configurations including a photovoltaic system and battery storage, the electrical energy balance is extended to:

$$PV_t^{\text{used}} + BA_t^{\text{out}} + GR_t^{\text{used}} = HH_t + \frac{\dot{Q}_{\text{HP}}(t)}{COP_t} + BA_t^{\text{in}}, \tag{8}$$

where BA_t denotes electric power in and out of the battery, GR_t the electric power from the grid, and HH_t the measured household electricity load excluding the heat pump. The battery state of charge and power constraints are given by:

$$SOC_t^{\text{bat}} = SOC_{t-1}^{\text{bat}} + \eta \cdot BA_t^{\text{in}} - \frac{BA_t^{\text{out}}}{\eta}, \qquad 0 \leq SOC_t^{\text{bat}} \leq CAP^{\text{bat}}, \qquad 0 \leq BA_t^{\text{in}}, BA_t^{\text{out}} \leq BA_{\max}, \tag{9}$$

with a round-trip efficiency of $\eta = 0.95$, a usable capacity of $CAP^{\text{bat}} = 10$ kWh, and a maximum charge/discharge power of $BA_{\max} = 4$ kW. Feed-in remuneration for surplus PV generation is not modeled, as typical German feed-in tariffs lie substantially below retail electricity prices; only self-consumed PV generation is therefore credited.

2.2. Optimization framework

System operation is optimized by minimizing total electricity costs while satisfying thermal comfort and technical constraints over a full calendar year. The optimization is performed on a rolling daily horizon, with the indoor temperature and storage states at the end of each day carried forward as initial conditions for the following day, ensuring temporal consistency of temperature trajectories and storage levels across the simulation period.

For configurations without PV and battery storage, the objective function minimizes heat pump electricity costs:

$$\min \sum_t \left(\left(\frac{\dot{Q}_{\text{HP}\rightarrow\text{SH}}(t) + \dot{Q}_{\text{HP}\rightarrow\text{Tank}}(t)}{COP_t} \right) p_t + \lambda \cdot \text{offPenalty}_t \right), \tag{10}$$

where p_t is the hourly spot market electricity price and λ a weighting factor for the optional short-cycling penalty term. For PV-coupled configurations, the objective is extended to minimize total grid electricity costs of the household:

$$\min \sum_t \left(\mathrm{GR}_t^{\mathrm{used}} \cdot p_t \; + \; \lambda \cdot \mathrm{offPenalty}_t \right). \tag{11}$$

The cycling penalty term $\mathrm{offPenalty}_t$ discourages excessive compressor start-stop behavior and is linked to the binary on/off state variable $y_t \in \{0, 1\}$ of the heat pump through:

$$\mathrm{offPenalty}_t \geq 1 - y_t. \tag{12}$$

The penalty is applied only in designated scenarios with cycling constraint active (mTV variants) and is excluded from final cost reporting; only actual energy costs enter the evaluation metrics.

The optimization is subject to the following constraints. The indoor temperature must remain within a seasonally adjusted comfort band in accordance with DIN EN ISO 7730:

$$20\,^{\circ}\mathrm{C} \leq \theta_t \leq 22\,^{\circ}\mathrm{C} \qquad \text{(heating season: October–April)}, \tag{13}$$

$$17\,^{\circ}\mathrm{C} \leq \theta_t \leq 25\,^{\circ}\mathrm{C} \qquad \text{(non-heating season)}. \tag{14}$$

A daily energy balance constraint ensures that the total heat supplied by the heat pump over each day equals the measured daily heat demand, preventing the optimizer from systematically exploiting comfort band flexibility to underprovide heat:

$$\sum_{t \in \mathcal{T}_d} \left(\dot{Q}_{\mathrm{HP} \to \mathrm{SH}}(t) + \dot{Q}_{\mathrm{Tank} \to \mathrm{SH}}(t) \right) = \sum_{t \in \mathcal{T}_d} \dot{Q}_{\mathrm{demand}}(t), \tag{15}$$

where $\mathcal{T}_d$ denotes the set of hourly time steps within day d. Additional constraints enforce the heat pump modulation bounds Eq. (5), the buffer storage dynamics Eqs. (6) and (7), battery dynamics Eq. (9), and the maximum observed heat pump output as an upper bound on thermal power.

The model is formulated as a mixed-integer linear program (MILP), with one binary variable per time step representing the on/off switching state of the heat pump. The implementation uses Python with the Pyomo algebraic modeling framework; the CBC solver is employed for all simulation runs.

2.3. Data sources and parameter assumptions

Measurement data were provided by a German heat pump manufacturer and cover the full calendar year 2024. The dataset contains hourly time series of thermal energy output, electrical energy consumption, PV generation, battery state of charge, household electricity load, and grid exchange for real residential heat pump installations. Data preprocessing comprised removal of erroneous measurements, hourly aggregation using a proprietary manufacturer function, and imputation of missing electricity price values with a fallback price of 0.30 €/kWh.

Hourly day-ahead electricity prices for the DE-LU bidding zone were retrieved from the ENTSO-E Transparency Platform for 2024, reflecting real spot market conditions including pronounced morning and evening price peaks that correlate inversely with wind and solar generation. The cost assessment is based exclusively on spot market prices and does not include grid fees, levies, or taxes, which are fixed components independent of hourly dispatch decisions.

The data-driven COP time series, Eq. (4), is computed from the measurement records for each system individually. The measured operational baseline—the actual hourly dispatch observed in the field—serves as both the reference cost benchmark and the source of key system parameters, including peak thermal output and annual heat demand. Thermal building parameters follow DIN EN ISO 52016-1 for effective heat capacities and DIN EN ISO 7730 for comfort temperature ranges. Buffer storage parameters are based on manufacturer datasheets; battery parameters represent typical residential lithium-ion specifications. An overview of the key model parameters is given in Table 3 in appendix.

2.4. System scenarios and sensitivity analysis

A total of 48 system configurations are systematically evaluated, covering all combinations of heat pump type (ASHP, GSHP), heat distribution system (radiator, underfloor heating), optional thermal buffer storage (with/without), and building thermal mass class (light, medium, heavy). For PV-coupled scenarios, air-to-water heat pumps are combined with a 10 kWh battery and a rooftop PV system. An overview of all considered system combinations is given in Table 1.

Each system configuration is analyzed in four operational variants: without buffer storage and without cycling constraint (oSP/oTV), representing the theoretical maximum of achievable cost savings; without buffer storage but with cycling constraint (oSP/mTV); with buffer storage but without cycling constraint (mSP/oTV); and with both buffer storage and cycling constraint (mSP/mTV). The oSP/oTV variant thus defines an idealized performance

Table 1: Overview of investigated system combinations.

System	Distribution	Buffer storage	Building mass
ASHP	Radiator	with / without	light / medium / heavy
ASHP	Underfloor heating	with / without	light / medium / heavy
GSHP	Radiator	with / without	light / medium / heavy
GSHP	Underfloor heating	with / without	light / medium / heavy
ASHP + PV + Battery	Radiator	with / without	light / medium / heavy
ASHP + PV + Battery	Underfloor heating	with / without	light / medium / heavy

upper bound, while variants including the cycling constraint reflect more realistic operating conditions by suppressing excessive compressor switching.

Sensitivity analyses are conducted by systematically varying the effective thermal heat capacity (representing uncertainty in building characterization), the buffer storage volume and loss coefficient, the thermal comfort band width, and historical electricity price profiles spanning 2019–2024. All other parameters are held constant in each sensitivity run, permitting the marginal influence of individual model assumptions to be assessed in isolation. Results are reported on both hourly and daily aggregation levels to capture seasonal as well as intra-day flexibility patterns.

2.5. Model validation

Model validity is assessed along three dimensions. First, the daily thermal energy balance is verified across all simulated days to confirm that the optimizer does not systematically exploit comfort band flexibility to reduce heat supply below measured demand. Second, modeled indoor temperature trajectories are checked against the defined comfort bounds throughout the full year. Third, simulated cost reductions and energy flows are cross-checked against empirical baseline data for plausibility, and the sensitivity of results to key parameter variations is used as an indicator of model robustness.

Several limitations of the modeling approach must be acknowledged. The single-zone formulation neglects spatial temperature gradients within the building. Hydraulic distribution losses, domestic hot water provision, defrost cycles of air-to-water heat pumps, and utility-imposed grid lock-out periods are not represented. Feed-in compensation for PV surplus is not modeled. Accordingly, the reported savings potentials represent technically achievable upper bounds under the stated assumptions. Practical implementation additionally requires deployment of a smart meter and a home energy management system (HEMS) capable of real-time price-based dispatch.

3. Results

3.1. Cost savings and load shifting

Price-driven flexible operation enables significant temporal load shifting toward low-price periods across all system configurations. In the idealized scenario without cycling constraint (oSP/oTV), heat generation is strongly concentrated during hours of lowest day-ahead spot prices, achieving maximum cost reductions. For the air-to-water heat pump with underfloor heating (ASHP + UFH), the optimized dispatch shifts 5.5 to 7.5 MWh of annual heat production into low-price windows depending on building mass, yielding electricity cost savings of 22.5% to 34.4%. The corresponding reduction in electrical energy consumption reaches up to 8.3% in the most favorable cases, as load shifting concentrates operation at higher COP conditions.

Under the more realistic cycling-constrained variant (oSP/mTV), shifted heat quantities decline to approximately 4.4 to 5.8 MWh per year, while cost savings range from 11.7% to 19.4% for the same system type. Load profiles are visibly smoothed, with reduced peak amplitudes and more uniform intra-day heat generation, while cost reductions are largely retained. Across all system types and building mass categories, realistic savings (mTV variants) consistently fall in the range of 5% to 21%, as summarized in Table 2.

The mean daily load profiles confirm that flexible operation systematically shifts heat generation away from morning and evening price peaks toward midday and nighttime low-price windows. In winter, this leads to pronounced pre-heating cycles preceding peak price hours. In the shoulder season, frequent start-stop sequences characterize the unconstrained variants, while the cycling-constrained operation produces a smoother redistribution. Summer profiles show minimal shifting activity due to low heating demand.

3.2. Influence of building thermal mass

Building thermal mass is identified as the dominant factor governing flexibility potential across all system configurations. The effective heat capacity of the building, ranging from 4.58 kWh/K for light to 10.83 kWh/K for

Table 2: Cost savings given in % under cycling constraint (mTV) for all systems by building mass and buffer storage (oSP = without buffer, mSP = with buffer storage). ASHP = air-to-water heat pump, GSHP = brine-to-water heat pump.

System	**Distribution**	**Light**		**Medium**		**Heavy**	
		oSP	**mSP**	**oSP**	**mSP**	**oSP**	**mSP**
ASHP	Underfloor heating	11.7	12.5	16.6	16.8	19.4	19.3
ASHP	Radiator	11.3	12.4	13.0	13.8	14.3	14.7
GSHP	Underfloor heating	5.2	6.2	10.1	10.5	12.1	11.9
GSHP	Radiator	9.4	7.0	10.0	7.3	10.7	7.4
ASHP + PV + Battery	Underfloor heating	18.6	19.8	19.2	20.8	20.3	21.8
ASHP + PV + Battery	Radiator	17.0	15.3	17.0	15.4	17.6	16.0

heavy construction (DIN EN ISO 52016-1), determines the extent to which heat generation can be temporally decoupled from heat demand.

For the ASHP + UFH system in the idealized scenario, cost savings increase from 22.5% (light) to 29.6% (medium), and 33.8% (heavy building). Under the realistic cycling-constrained operation, the spread narrows but remains substantial: 11.7% (light) versus 19.4% (heavy). The same monotonic trend is observed for all other heat pump and distribution system combinations. Heavy buildings allow heat loads to be shifted over longer time windows, enabling the optimizer to exploit price differentials more effectively. Sensitivity analyses confirm that the effective thermal capacity is the most influential single model parameter: a ±50% variation of the building heat capacity produces savings changes of up to ±6 to 8 percentage points, depending on the operating variant.

Underfloor heating systems benefit from additional thermal inertia provided by screed mass, captured via construction-class-specific scaling factors (f_{UFH} = 1.6 to 2.2). This effectively increases the available heat storage capacity compared to radiator systems, contributing to higher shifting potential for UFH configurations. In contrast, radiator systems exhibit more pronounced load peaks and a narrower time window for effective load shifting.

3.3. Effect of thermal buffer storage

The contribution of the 400-liter buffer storage (approximately 2.27 kWh usable capacity) to overall cost savings is limited and varies by system configuration. For ASHP + UFH, the addition of buffer storage yields only marginal improvements: savings under the mSP/oTV variant differ from the oSP/oTV baseline by less than 1 percentage point in most building mass categories, and in several cases the buffer storage slightly increases costs due to thermal losses. This redundancy arises because underfloor heating systems already provide substantial inherent thermal inertia through screed mass, effectively rendering the additional water storage superfluous.

For radiator systems, the picture is more differentiated. The ASHP + radiator combination shows a moderate positive effect of buffer storage under idealized conditions (e.g., savings increase from 18.4% to 20.1% for light buildings in the oTV variant). However, for GSHP + radiator systems, buffer storage consistently reduces net cost savings across all building mass categories and operating variants, as the optimizer shifts heat generation into favorable low-price but COP-unfavorable hours, and storage losses negate any additional gains. In PV-coupled configurations, the buffer storage yields a clear positive effect for UFH systems (savings improving by approximately 1 to 2 percentage points), but has neutral or slightly negative effects for radiator systems. The sensitivity of results to buffer storage volume and loss coefficient is low in all configurations, confirming that the storage size is not a critical design parameter within the simulated range.

3.4. PV and battery coupling

Integration of a rooftop PV system and a 10 kWh battery storage unit substantially enhances the economic performance of flexible heat pump operation by enabling self-consumption of solar electricity and reducing grid interaction costs. For the ASHP + PV + Battery + radiator configuration, cost savings under realistic operating conditions (mTV) range from 15.3% to 17.6% across building mass classes, compared to 11.3% to 14.7% for the standalone ASHP + radiator system. The most favorable outcomes are achieved for the ASHP + PV + Battery + UFH combination, with idealized savings reaching 37.4% to 39.8% and realistic savings of 18.6% to 21.8%, the highest of all investigated configurations.

The synergistic effect of PV coupling is most pronounced during summer and transition seasons, when midday solar generation coincides with low spot market prices. The optimizer concentrates heat pump operation in these hours, simultaneously exploiting self-consumption and price advantages. In the unconstrained variant, net grid consumption is reduced by 3.8% to 6.9% on average, while cost reductions reach 35% to 41%. The cycling-constrained variant, however, leads to grid consumption increases of 19% to 23% due to more uniform operation across extended low-price periods, while still yielding savings of 15% to 22%. Battery storage contributes to smoothing PV feed-in and enabling time-shifted self-consumption, particularly on cloudy days and during evening hours.

3.5. Sensitivity and volatility analysis

Sensitivity analyses confirm the robustness of the results with respect to key model parameters. The effective thermal heat capacity of the building zone exerts the strongest influence on achievable savings, followed by buffer storage volume, while storage loss coefficients have negligible effects. Across all four operating variants, a 50% reduction in effective heat capacity reduces savings by 4 to 8 percentage points for UFH systems, underlining the central role of building construction quality.

The volatility analysis covers GSHP + UFH operation across the years 2019 to 2024, using historical day-ahead spot prices from the DE-LU bidding zone. The results do not show a strong direct correlation between annual price volatility (measured as average daily standard deviation) and achieved savings. Notably, savings in 2022—the year of highest price volatility—are lower than in 2020; this is attributed to higher energy price levels and the constraint that daily heat demand must be fully met. For unconstrained variants (oSP), a slightly negative correlation with annual volatility is observed, while constrained variants with buffer storage (mSP) show a weak positive relationship. This indicates that the instantaneous price level at the time of heating demand and the structure of intra-day price differentials in adjacent hours are more decisive than aggregate annual volatility metrics for determining realized savings.

4. Discussion

4.1. Technical and practical feasibility

The results demonstrate that price-based flexible heat pump operation is technically feasible and economically beneficial under real market conditions, provided that appropriate control infrastructure is in place. The unconstrained operating variants define a theoretical performance ceiling that would require accepting very high compressor cycling rates—on the order of several start-stop cycles per hour during transition seasons—which would cause excessive wear and efficiency losses not captured in the present model. The cycling-constrained variants, which approximate realistic smart control behavior by penalizing frequent switching, show that meaningful savings of 5% to 21% remain achievable with smoother load profiles, while reducing mechanical stress on the compressor.

Implementation of such strategies requires a smart electricity meter and a home energy management system (HEMS) capable of retrieving hourly day-ahead prices and dispatching the heat pump accordingly. Both components are increasingly available in the German residential market, with smart meter rollout progressing under regulatory mandates. Dynamic electricity tariffs, directly linked to spot market prices, are a prerequisite for households to capture the modeled savings. While such tariffs are currently offered by a growing number of suppliers, broad consumer adoption remains limited, partly due low smart meter penetration rate across Germany, to risk perception, and finally the lack of awareness of potential benefits. Practical deployment must also account for utility-imposed grid lock-out periods and local network constraints, which were not modeled here and may reduce available flexibility windows.

A key finding with practical implications is the dominant role of building thermal mass. Unlike buffer storage—which can be added as a hardware component—building mass is largely determined by construction type and is difficult to modify in existing stock. This suggests that flexible heat pump control is most valuable in medium and heavy-mass buildings, which includes a large share of the existing German building stock, while light-mass construction imposes inherent limitations on shifting potential. For new constructions and deep renovations, this finding supports designing for higher thermal mass as a co-benefit for demand-side flexibility.

The limited and configuration-dependent value of buffer storage is a notable finding that diverges from some prior assessments. While small buffer tanks can provide marginal benefits in specific configurations—particularly for radiator systems with low inherent thermal inertia—they introduce heat losses and in some cases reduce net savings. This result suggests that buffer storage sizing and deployment should be carefully evaluated in the context of the specific heating system and building type, rather than assumed to be universally beneficial.

4.2. Market and policy implications

Dynamic electricity tariffs emerge as the key enabling mechanism for household-level flexibility, creating direct financial incentives aligned with system-level needs. The demonstrated savings potential of 5% to over 20% under realistic assumptions represents a meaningful contribution to reducing household heating costs, which could materially improve the economics of heat pump adoption and address one of the main barriers identified in consumer surveys. Virtual power plant (VPP) operators could additionally monetize residential heat pump flexibility in intraday energy markets or balancing markets, providing another revenue stream that was not quantified in this study.

4.3. Comparison with literature

The reported savings range of 5% to 21% under realistic operating conditions is broadly consistent with findings from prior modeling studies, which typically report flexibility-driven savings of 5% to 25% for residential heat pumps under various European price regimes. The upper range of 30% or more in the idealized scenarios aligns with maximum values reported in the literature for unconstrained optimization. A direct comparison with Ali et al. [16], who report savings of up to 46%, reveals methodological differences: their analysis focuses on single representative days, whereas the present work evaluates full annual operation, which inherently reduces average savings due to periods of low price spread and binding thermal comfort constraints. Furthermore, the present study identifies the buffer storage effect as configuration-dependent and sometimes negative for GSHP systems, a nuance not consistently addressed in prior work. The use of real operational COP data from 2024 measurements, rather than modeled or synthetic efficiency curves, is a key differentiator that captures actual part-load behavior and seasonal variation under current market conditions.

5. Conclusion

This study quantifies the economic potential of flexible, price-driven operation of residential heat pumps using real operational data from 2024, covering 48 system configurations across heat pump types, heat distribution systems, building mass categories, and optional system components. The results confirm that price-based load shifting yields cost savings of up to 30% in idealized scenarios and 5% to 21% under realistic operating conditions that limit compressor cycling. Building thermal mass is identified as the dominant driver of flexibility potential, with heavy-mass buildings outperforming light-mass constructions by up to 8 percentage points in achievable savings. Buffer storage provides only marginal or occasionally negative contributions, particularly for underfloor heating systems where the inherent thermal inertia of screed already provides sufficient shifting capacity. PV coupling proves most beneficial for self-consumption optimization and achieves the highest overall savings of up to 41% in combined configurations. These findings provide a quantitative foundation for the design of dynamic tariff models, smart home energy management systems, and demand-side flexibility programs, and demonstrate that flexible heat pump control is both technically feasible and economically attractive under current German market conditions.

Future work should address the integration of occupant behavior and probabilistic comfort models, the incorporation of CO_2 intensity signals alongside price signals for carbon-aware dispatch, the extension to additional flexible loads such as domestic hot water preparation and electric vehicles, and the development of real-time control prototypes validated against measured operational data. Increasing the time resolution to 15-minute intervals would additionally enable assessment of intraday market participation opportunities beyond day-ahead price optimization.

CRediT author statement

Jendrik Kasper: Conceptualization, Methodology, Software, Validation, Formal analysis, Data Curation **Mathias Hofmann:** Conceptualization, Writing - Original Draft, Writing - Review & Editing, Visualization, Resources, Supervision **Janosch Balke:** Conceptualization, Data Curation, Resources, Supervision **Stefan Elbel:** Supervision **Katharina Herkendell:** Resources, Supervision

Acknowledgments

Jendrik Kasper thanks the supporting heat pump manufacturer for providing real operational data. The authors used the DeepL-Write, ChatGPT and Grammarly models for language correction and thoroughly reviewed and edited the content, taking full responsibility for the accuracy and integrity of the text.

Nomenclature

Abbreviations

ASHP Air-to-water heat pump

GSHP Brine-to-water heat pump

mSP With buffer storage

mTV With cycling constraint

oSP Without buffer storage

oTV Without cycling constraint

PV Photovoltaic

UFH Underfloor heating

Letter symbols

A Floor area, m^2

BA Electric power in and out of the battery, W

c Heat capacity, kWh/K

CAP Storage capacity, kWh

COP Coefficient of performance, –

f Construction-class-specific scaling factor, –

GR Electric power from the grid, W

HH Measured household electricity load, W

k Coefficient, –

p Spot market electricity price, €/kWh

P Electrical power, W

$\dot{Q}$ Heat rate, W

SOC State of charge, kWh

t Time, h

V Volume, L

y Binary variable, –

Greek symbols

Δ Difference, –

η Round trip efficiency, –

λ Weighting factor, –

θ Indoor air temeperature, °C

Subscripts and superscripts

0 Initial

bat Battery

eff Effective

HP Heat pump

in To storage

loss Heat loss

max Maximum

out From storage

SH Space heating

t Time step index

Tank Water tank

used Used electricity

References

[1] Bundesverband Wärmepumpe (BWP). *Absatzstatistik Wärmepumpen Deutschland 2024*. Berlin, Germany: BWP, 2025.

[2] Bundesministerium für Wirtschaft und Klimaschutz (BMWK). *Gebäudereport 2024 – Daten und Trends zur Entwicklung des Gebäudebestands*. Berlin, Germany: BMWK, 2024.

[3] European Commission. *A Renovation Wave for Europe – Greening Our Buildings, Creating Jobs, Improving Lives*. Brussels, Belgium, 2020.

[4] Bundesverband der Energie- und Wasserwirtschaft (BDEW). *Energiewende im Gebäudesektor – Akzeptanz und Hemmnisse*. Berlin, Germany, 2024.

[5] International Energy Agency (IEA). *Electricity Market Report 2024*. Paris, France, 2024.

[6] H. Lund et al. “Renewable energy systems – A smart energy systems approach to the choice and modelling of 100% renewable solutions”. In: *Chemical Engineering Transactions* 81 (2020), pp. 1–6. DOI: 10.3303/CET2081001.

[7] M. Perez, J. A. Meeus, and L. Olmos. “Demand-side flexibility: A key enabler of a renewable-based power system”. In: *Energy Policy* 138 (2020), p. 111231. DOI: 10.1016/j.enpol.2019.111231.

[8] S. Arteconi, N. J. Hewitt, and F. Polonara. “Domestic demand-side management (DSM): Role of heat pumps and thermal energy storage (TES) systems”. In: *Applied Thermal Engineering* 51.1–2 (2013), pp. 155–165. DOI: 10.1016/j.applthermaleng.2012.09.023.

[9] J. Salpakari and P. Lund. “Optimal and rule-based control strategies for energy flexibility in buildings with PV”. In: *Applied Energy* 161 (2016), pp. 425–436. DOI: 10.1016/j.apenergy.2015.10.036.

[10] A. Papaefthymiou, S. Hasche, and C. Nabe. “Potential of heat pumps for demand side management and wind power integration in the German electricity market”. In: *IEEE Transactions on Sustainable Energy* 3.4 (2012), pp. 636–642. DOI: 10.1109/TSTE.2012.2202132.

[11] T. Schütz, J. Schröder, M. Fuchs, and H. Müller-Steinhagen. “Demand side management of heat pumps using model predictive control”. In: *Energy Procedia* 158 (2019), pp. 3443–3448. DOI: 10.1016/j.egypro.2019.01.902.

[12] K. Hedegaard and A. N. Andersen. “Role of heat pumps and thermal storage in future energy systems”. In: *Energy* 184 (2019), pp. 408–419. DOI: 10.1016/j.energy.2019.06.171.

[13] A. Bloess, W.-P. Schill, and A. Zerrahn. “Power-to-heat for renewable energy integration: A review of technologies, modeling approaches, and flexibility potentials”. In: *Applied Energy* 212 (2018), pp. 1611–1626. DOI: 10.1016/j.apenergy.2017.12.073.

[14] F. Kensby, A. Trüschel, and J.-O. Dalenbäck. “Potential of residential buildings as thermal energy storage in district heating systems – Results from field measurements”. In: *Energy and Buildings* 82 (2014), pp. 155–163. DOI: 10.1016/j.enbuild.2014.07.026.

[15] A. Zerrahn and W.-P. Schill. “Long-run power storage requirements for high shares of renewables: Review and a new model”. In: *Renewable and Sustainable Energy Reviews* 79 (2017), pp. 1518–1534. DOI: 10.1016/j.rser.2017.05.145.

[16] M. Ali, J. Jokisalo, K. Siren, and M. Lehtonen. “Combining the Demand Response of direct electric space heating and partial thermal storage using LP optimization”. In: *Electric Power Systems Research* 106 (2014), pp. 160–167. DOI: 10.1016/j.epsr.2013.08.017.

A Appendix

Table 3: Key model parameters and their values.

Parameter	Symbol	Value	Unit
Building thermal model			
Effective heat capacity (light)	$c_{\text{eff,light}}$	4.58	kWh/K
Effective heat capacity (medium)	$c_{\text{eff,medium}}$	6.88	kWh/K
Effective heat capacity (heavy)	$c_{\text{eff,heavy}}$	10.83	kWh/K
UFH scaling factor (light/medium/heavy)	f_{UFH}	1.6 / 2.0 / 2.2	—
Buffer storage			
Tank volume	V	400	L
Temperature lift	ΔT	5	K
Storage capacity	CAP	2.27	kWh
Loss coefficient	k_{loss}	0.075	kWh/h
Initial state of charge	SOC_0	$0.5 \cdot CAP$	kWh
Battery storage			
Usable capacity	CAP^{bat}	10	kWh
Max. charge/discharge power	BA_{max}	4	kW
Round-trip efficiency	η	0.95	—
Initial state of charge	$\text{SOC}_0^{\text{bat}}$	$0.5 \cdot E^{\text{bat}}$	kWh
Optimization			
Time resolution	Δt	1	h
Fallback electricity price	p_{fallback}	0.30	€/kWh
Initial indoor temperature	θ_0	21	°C
Solver	—	CBC	—