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Aggregator electricity price guarantees for households with flexibility potential utilizing thermal building inertia

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HIGHLIGHTS

- Developed a three-stage method to calculate price guarantees under uncertainty.
- Aggregators guarantee individual fixed tariffs for constrained control of flexibility.
- Monte Carlo simulation of 9404 households with varying endowments and preferences.
- Aggregator-control reduced electricity costs by an average of 7.36% (2.5 ct/kWh).
- Building characteristics strongly shape flexibility potential and guarantee values.

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ABSTRACT

This study introduces an approach to mitigate the reluctance of households to adopt dynamic electricity tariffs by proposing individual price contracts tailored to household characteristics. These contracts guarantee individual electricity rates to households with flexibility potential, such as thermal or electrical storage and the thermal mass of buildings, in exchange for granting aggregators operational control. The household-specific contracts are determined and evaluated through a three-step process, combining deterministic and stochastic modeling. First, an optimization problem for the operation of home energy management systems is formulated. The proposed model incorporates the thermal inertia of buildings as a flexibility potential, an aspect frequently overlooked in existing studies. Then, a Monte Carlo simulation of household parameter combinations is run, followed by a quantile regression prediction of household-level low-price guarantees. The simulations of 9404 household configurations in Germany demonstrate that aggregator-managed flexibility consistently lowered electricity costs by an average of 7.36% (2.5 ct/kWh) compared to static tariffs, with 78.4% of households achieving rates below the competitive retail benchmark. Aggregators also realized higher profitability on a per-household basis across all three analyzed years compared to scenarios without flexibility control. Our results demonstrate that building parameters, particularly thermal inertia, substantially influence the available flexibility potential and should be considered a key factor in the design of household-level guarantee contracts. The study contributes to understanding and quantifying uncertainty in dynamic tariffs for households, aiming to advance the utilization of household demand response potential in modern power markets.

1. Introduction

The sharp increase in intermittent renewable energy generation in the power systems of many countries requires an expansion of demand-side flexibility capacity [58]. Besides the ramp-up of battery storage capacity, household demand response is an integral tool to increase this flexibility [2].

One widely discussed policy option to encourage demand response is the introduction of dynamic tariffs for electricity consumers to signal temporal scarcity and provoke a response from flexible loads. While there are various possible implementations of dynamic tariffs (e.g., time-of-use, critical peak pricing, real-time prices, etc.), their underlying rationale is the same: Customers pay time-variable prices for their

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consumption that are aligned with power system scarcity signals [34]. The operation of home energy management systems in the context of these dynamic electricity tariffs has been widely studied from an operations research perspective, with a focus on improving energy scheduling and cost management [4,42].

Despite their potential benefits, the adoption of dynamic electricity tariffs remains limited in most major markets. A recent survey in Germany revealed that only 7% of households have subscribed to such tariffs [85]. While in theory, dynamic tariffs enable an alignment of consumer demand and market signals [35], consumers are reluctant in their adoption [62]. A UK study found that two-thirds of households would not switch to a time-of-use dynamic tariff, with loss aversion being one of the most prominent drivers of this reluctance [62].

Literature suggests that the limited adoption of dynamic tariffs is fundamentally rooted in uncertainty [77]. For households, uncertainty about future electricity prices and potential savings contributes to reluctance in adoption, driven by behavioral factors such as loss aversion. The growing installation of electricity-based heating systems, such as heat pumps, could further exacerbate this uncertainty. These systems introduce additional complexities for home energy management, requiring models to account for temperature-dependent heat pump efficiencies and the thermal inertia of buildings, which is influenced by insulation properties [32,76].

While households may be hesitant to adopt dynamic tariffs due to risk aversion and uncertainty, aggregators offer a viable mechanism to address these challenges [16]. Aggregators are entities that pool and manage decentralized flexibility resources, acting as intermediaries between end-users and electricity markets to optimize market participation [16]. While significant progress has been made in developing algorithms and operational strategies for aggregators to manage decentralized fleets of households equipped with battery storage [5] or heat pumps [49,94], a unified and comprehensive formulation of the operational problem for households under dynamic tariffs remains an open challenge. Existing studies do not fully integrate the interaction of PV and battery energy storage (BESS) systems [78], heat pumps, and insulation-dependent thermal inertia of buildings [76], as well as the uncertainties associated with occupant heating behavior and comfort preferences [9]. This gap in the literature creates uncertainty for aggregators, complicating their ability to accurately evaluate and harness the flexibility potential of residential energy systems.

Our study seeks to address the barriers to dynamic tariff adoption by mitigating uncertainties for both households and aggregators. We propose introducing low-price guarantee contracts for households, which secure a fixed cost per unit of electricity below the benchmark tariff, in exchange for granting aggregators control over household flexibility. In other domains, such as logistics, services, or finance, guarantee schemes have been established for mitigating risks [55,74,80]. The suggested guarantees, offered by aggregators, provide households with a predictable cost framework by transferring the associated risks of dynamic tariffs and volatile electricity prices to the aggregator. In exchange, the aggregator gains operational control over the households' flexibility potential. To address the uncertainties faced by aggregators, we develop a comprehensive formulation of household flexibility potential, integrating factors such as energy storage, thermal building inertia, and occupant behavior. This formulation enables a more accurate estimation of the value derived from managing residential flexibility. The proposed system is then utilized to design household-level low-price guarantees while quantifying the associated risks and profit potentials for aggregators.

Summarizing, price uncertainty is a significant barrier to the widespread adoption of dynamic tariffs and, consequently, household demand response programs. Households may be discouraged by the risk of unpredictable price fluctuations, while aggregators may avoid offering guarantees due to the difficulty of accurately modeling household flexibility across electrical, thermal, and behavioral dimensions. This motivates our overarching research question, which is stated as follows.

Research Question. Under realistic conditions, is there an economic incentive for aggregators to offer customers guaranteed prices at attractive rates, in exchange for the right to operate their flexibility potential?

Research Method. We model German household energy-related configurations, including thermal building dynamics, heat pumps, battery and thermal storage systems, and PV installations, while incorporating household preferences such as thermostat setpoint profiles and flexibility allowances. Using historical weather and electricity price data, we optimize household energy management through a three-stage process: first, formulating a home energy management optimization problem, then conducting a Monte Carlo simulation of 9404 household parameter combinations, and finally applying quantile regression to predict household-specific electricity price guarantees that aggregators can offer in exchange for operational control over flexibility potential.

Summary of Findings. Our study demonstrates that aggregator control of household flexibility potentials reduces electricity costs by an average of 7.36% (2.5 ct/kWh) in our simulation compared to static tariffs, with 78.4% of households achieving rates below the competitive retail benchmark price. Aggregators also achieve improved financial outcomes at the household level, albeit with a moderately wider confidence interval. The analysis reveals that thermal building dynamics, particularly insulation levels and modernization status, are important factors influencing price guarantee levels and household flexibility potential. These findings support the development of decision support systems capable of offering low-price guarantees tailored to individual household characteristics, demonstrating a viable path for transferring price risk from households to aggregators while maintaining mutual benefits.

Our methodology for formulating individual, household-level low-price guarantees is based on a three-stage process. First, given a certain household setup and corresponding spot market prices, we formulate a model to calculate the achievable electricity prices. A household setup consists of endowment (e.g., size of heat pumps, PV, BESS, etc.), heating requirements, building insulation, household load profiles, and local weather profiles. Second, we simulate randomly drawn household setups and calculate corresponding possible guarantee prices. The first two stages are simulated under perfect foresight, i.e., we know exact household load curves, price profiles, weather measurements, heating setpoints, and PV generation for the investigated years. In the third stage, we implement a model to suggest actual low-price guarantees. To this end, we train a forecasting model based on input features that are observable characteristics (e.g., household endowment) and aggregate price information (mean annual day-ahead market price, i.e., a yearly power future price). The model cannot access actual market price curves, weather profiles, PV generation, and heating setpoints. The decision problem directly models the uncertainty aggregators face when offering individual price guarantees in exchange for household flexibility potential. It captures real-world complexities such as variable consumption patterns, fluctuating market prices, and differing household endowments, aligning closely with the practical challenges of implementing such guarantees. We then evaluate the associated risks for aggregators and assess the features influencing the level of potential price guarantees.

Overall, our study makes the following key contributions:

- **General contribution:** We address the gap between the theoretical flexibility potential of residential energy systems and the observed reluctance of households to adopt dynamic tariffs in practice. Our approach introduces a comprehensive modeling framework for home energy management systems, explicitly incorporating thermal building inertia and behavioral constraints. To mitigate the uncertainty that hinders adoption, we propose a novel mechanism of household-level electricity price guarantees. These guarantees provide cost predictability for households while enabling aggregators to harness residential flexibility potential, effectively lowering barriers to dynamic tariff adoption and fostering greater alignment between consumer behavior and market signals.

- **Specific contribution (1):** We formulate a comprehensive cost minimization framework for dynamic tariffs, integrating diverse flexibility potentials. These include PV generation, battery storage, thermal storage, and the often-overlooked impact of building-level insulation and modernization status on thermal inertia. Additionally, we account for behavioral constraints such as occupant-defined setpoint profiles. This holistic approach combines technical and behavioral dimensions to more accurately capture the real-world flexibility potential of households, providing a practical basis for effective demand-side management strategies.
- **Specific contribution (2):** We quantify the value generated for aggregators through the acquisition and management of household flexibility, providing a detailed assessment of the economic benefits derived from the suggested guarantees.
- **Specific contribution (3):** We predict and interpret household-level electricity price guarantees using a quantile regression approach and evaluate their reliability to ensure effective mitigation of uncertainty and financial losses for aggregators.

This article is structured as follows: Section 3 presents the proposed guarantee prediction methodology, which adapts a sector-agnostic guarantee-giving scheme to the context of electricity price guarantees. We detail our home energy management system optimization model, which integrates household flexibility potential and operational constraints into the decision-making process. In addition, we describe the Monte Carlo simulation process, the utilized quantile regression method, and how we evaluate the associated risks of given guarantees. Section 4 describes our model parametrization. In particular, we introduce the building typology that serves as input for our thermal building models, heat pump and thermal storage sizing decisions, empirical setpoint data, and real-world distributions of PV and BESS installations, as well as price and weather data. Section 5 presents the results of the model parametrization. We start with a validation of the modeled behavior of home energy management systems and benchmark it against actual empirical data of the German building stock. We then evaluate the calculated price guarantees. Finally, we investigate the factors that influence the level of price guarantees. In Section 6, we discuss the implications of our study and conclude in Section 7.1.

2. Related work

The literature has widely discussed the operational household flexibility potential with dynamic tariffs to achieve cost savings. The same is true for providing guarantees under uncertainty. This subsection summarizes past studies' main findings and illustrates the corresponding research gap.

Operating household electricity consumption under dynamic tariffs: Numerous studies investigate households subscribing to dynamic tariffs. These studies can be divided into two main groups. First, studies that focus on the overall scheduling problem of flexibility potential, such as battery storage, electric vehicles, and heat pumps [65,67,96]. Second, studies that investigate the policy implications of dynamic tariff adoption on an electricity system or grid [79].

The literature on load scheduling under dynamic tariffs aims at optimizing the dispatch of flexibility potential for household cost minimization [65,67,96]. For instance, battery storage systems can be scheduled with genetic algorithms to shift loads to lower price periods [67], electric vehicle charging events can be scheduled to accommodate user convenience and dynamic price variations [96] or heat pumps can be operated to shift the heating demand based on temperature constraints and day-ahead prices [63,65]. Some studies combine the flexibility of different appliances, e.g., by developing control algorithms for an all-electric dwelling with a heat pump, PV, thermal storage, and an electric vehicle [66]. While these studies contribute to the overall understanding of the operation of home energy management systems under dynamic pricing, they are mostly tailored to specific use cases, such as an Italian office building [65] or a residential building in Ireland [66]. However, to provide a generic price guarantee model for households with flexibility potential, an optimization model of a home energy management system is required that considers the varying building structures, heating patterns, and installed flexibility potential. Studies considering multiple sources of flexibility (e.g., electric vehicles, PV, and BESS installations) frequently apply a simplified heating model that only considers a singular building type and heating profile [6,78]. Yet, the load-shifting potential of buildings heavily varies across insulation standards [76]. To this end, reduced-order thermal response models (also called RC models) are described as viable ways to model the electrical heating demand of different building structures [76].

One noteworthy study from [91] contributes to the field by proposing and evaluating profile contracts as a mechanism to balance flexibility incentives with price risk hedging for electricity consumers. Profile contracts are real-time tariffs with a hedging component, where customers agree on a fixed price for a predefined consumption profile. At the same time, deviations are settled at spot market prices, allowing for both price stability and dynamic flexibility incentives. Unlike profile contracts, which rely on predefined consumption profiles, we propose a framework that dynamically adjusts to individual household behaviors and external uncertainties, enabling a more granular and operationally flexible approach to balancing aggregator risks and consumer incentives.

Most of the aforementioned studies assume that households eventually *will* switch to dynamic tariffs. However, it is unclear if that is the case, given the reluctance of customers to expose themselves to price risks [62]. Hence, we explore in the following section the existing literature on the formulation of guarantees, which are used in other disciplines to transfer and mitigate risks.

Formulating Guarantees: Guarantees are employed across various industries through distinct mechanisms, each aimed at addressing specific risks and enhancing market competitiveness. For example, service time guarantees can provide a competitive advantage by differentiating a firm from its competitors [74], credit guarantees enable capital-constrained entities to secure loans by transferring risk to a guarantor [54,88], and performance guarantees for hybrid power plants facilitate financing by reducing uncertainty about future power output and revenues [1]. In these contexts, the guarantor enhances the attractiveness or accessibility of its products or services, while the counterparty benefits from risk mitigation. Typically, the risk is transferred to an entity that possesses the expertise to manage it, such as in China, where regulators require operators of peer-to-peer lending platforms to transfer credit risks to specialized guarantee providers [88]. A similar risk transfer underpins the approach proposed in our study. While households may lack the expertise or risk tolerance to handle the volatility of dynamic tariffs, aggregators and utilities are well-versed in managing and hedging such risks [12]. Although guarantees benefit all involved parties, the underlying risk remains and must be carefully modeled and analyzed. For instance, guaranteed service times may still be exceeded [74], borrowers may default on loans [54,88], and the guaranteed output of a power plant may fall short of expectations [1]. Therefore, robust risk modeling and analysis are essential to supporting informed decision-making. While such models have been developed and discussed in other fields, the specific problem of formulating guaranteed constant electricity prices in exchange for operating household flexibility potential has not yet been addressed. This problem is particularly challenging because it combines the complexity of optimization with various interconnected constraints and behavioral variability, while also incorporating unique operational restrictions like thermal inertia and the dynamic potential of household flexibility. These elements require a novel approach to

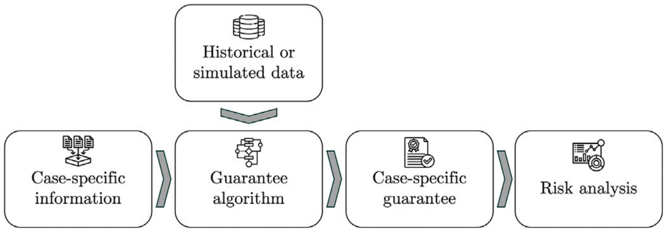


Fig. 1. Sector-agnostic guarantee-giving scheme.

balancing risk and resource allocation in a way that ensures both system reliability (e.g., thermal comfort of inhabitants) and economic viability (e.g., limited aggregator risk) under uncertainty. This study seeks to contribute to this research gap.

Based on existing guarantee-formulation literature, we devise a sector-agnostic scheme in Fig. 1, which is described as follows. It later serves as the foundation for our guarantee model [1,54,74,88].

First, a common denominator of guarantee literature is that **case-specific information** about the counterparty and the desired guarantee is ascertained and shared with the guarantee-giving entity. This can include system characteristics like the location or desired output of a power plant [1], fixed values for costs [54,56], or known probability functions for uncertain inputs like demand [54]. Then, a connection between the case-specific information and the output guarantee is established based on **historical or simulated data**. For instance, the underlying dataset can be built up by simulating a high number of scenarios, consisting of possible parameter combinations and uncertain input parameters [1,56]. Alternatively, an empirical dataset exists upon which the guarantees can be formulated [18]. We note that there are also studies that are not based on historical or simulated data, which formulate a mathematical case for a guarantee [80]. However, for problems with time-dependent systems and input parameters (like in our case), this is hardly possible. The actual relationship between case-specific information, potential historical or simulated data points, and viable guarantees is established with a **guarantee algorithm**. The selected algorithm depends on the context of the guarantee. When there is an interaction between the guarantee-giving entity and counterparty, the decision process is frequently modeled with a Stackelberg game [54,88]. When there is no interaction and the guarantee should be conditioned upon the previously simulated scenario data, a guarantee curve can be obtained with a linear optimization [1]. A guarantee curve illustrates the relationship between a guaranteed outcome given a varying input condition (i.e., guaranteed power output of a PV plant given varying irradiance levels). In other cases, an analytical guarantee formulation can be obtained [80]. Then, a **case-specific guarantee** is the output of the guarantee algorithm. This can either be a fixed-guarantee for given, case-specific input parameters [80], or a curve that describes varying guarantees conditioned on exogenous input parameters [1,54]. Eventually, the risk and competitiveness of the formulated guarantees are evaluated in a **risk analysis** step, which mostly focuses on describing the distribution of the results of the guarantees. This may include evaluating the mean of the distribution [1], confidence interval width [82], specific percentiles or Value-at-Risk measures [1,84], or the variance of the results [56].

In summary, prior research has contributed valuable insights into household flexibility under dynamic tariffs and into the design of guarantees and risk assessment across various domains. However, these two strands of literature have largely developed in parallel. Studies on home energy management and load scheduling typically optimize the dispatch of flexibility resources, but they often rely on simplified heating models or restrict the analysis to specific case studies, without capturing the heterogeneity of building structures and thermal inertia [6,76,78]. Conversely, the literature on guarantees has developed sophisticated mechanisms for transferring risks in other sectors [1,54,74,88], yet it has not addressed the problem of designing price guarantees for households exposed to dynamic electricity prices. This leaves a gap in integrating detailed household-level flexibility modeling with guarantee mechanisms that can mitigate price risks for consumers while managing aggregator exposure. We contribute to this gap by combining reduced-order thermal building models, empirical data on household flexibility potentials, and a quantile regression-based algorithm for individual guarantees.

3. Guarantee model

We adapt the previously introduced sector-agnostic framework for guarantee algorithms (Fig. 1) to the specific context of this study. In particular, we design an algorithm that proposes household-specific electricity price guarantees in exchange for granting the operator the right to manage the household's flexibility potential in accordance with the household's stated preferences.

The steps of the proposed method are illustrated in Fig. 2. At the core of this process is the observation of **household endowment and indoor temperature flexibility preferences**, which ultimately shape the flexibility potential of each household [76,78]. Household endowments encompass the building type, modernization measures (e.g., improved insulation), PV systems, BESS, heat pump installations, and thermal storage. Preferences determine whether and to what extent the household permits the operator to adjust its heating setpoint profile (e.g., lowering the indoor temperature during high-price periods). The operation of household flexibility potential is subsequently modeled as an optimization problem, which captures the household-level **home energy management optimization** process.

We divide the investigation period into training and evaluation years. From the training years, exact setpoint profiles, day-ahead prices (which serve as input for the utilization of flexibility potential), and weather data (outside temperature and solar irradiance) are known. Then, yearly household electricity costs under dynamic pricing can be calculated, given any combination of endowment and preferences. The resulting total household electricity costs can be divided by the total consumption to calculate a price per unit of consumed electricity, which could have been guaranteed to a household. To build up a historical dataset that can serve as input for the guarantee algorithm, a **Monte Carlo Simulation** of

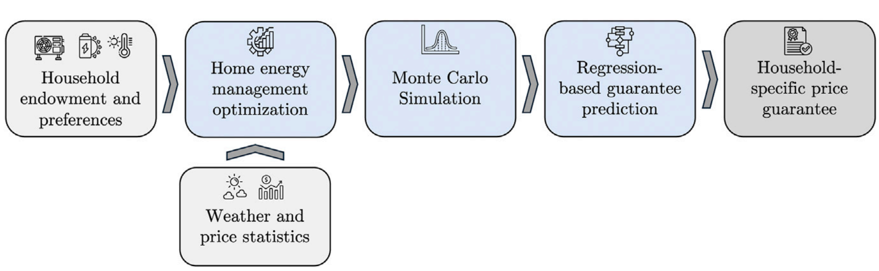


Fig. 2. Methodology to determine electricity price guarantees.

potential endowment, preference, geographical locations (which influence weather and irradiance), and historical price years is conducted. We resort to a stochastic Monte Carlo approach since calculating all possible parameter combinations would be computationally infeasible [1]. Although the Monte Carlo simulation inherently relies on random sampling, we use a structured procedure in which input parameters are drawn from predefined distributions, ensuring systematic coverage of the parameter space. In the resulting dataset, the actual weather and price time series are reduced to singular data points (average electricity price, average temperature), based on the assumption that aggregators can hedge future electricity prices through long-term electricity contracts or other procurement strategies[12] and make assumptions about future weather data. We note that hedging future electricity prices also incurs some costs, which are neglected in this study, since they occur under both the status quo without flexibility and guarantee contracts with flexibility. The generated datasets depict the relationship between household characteristics, spot market prices, weather, and potential price guarantees.

Then, the generated dataset is used to suggest price guarantees for the evaluation years based on randomly drawn combinations of endowment and preferences, and only the average spot market and weather data points for future years (given the assumption that the operator can hedge these). The underlying temperature setpoint profiles used in the evaluation period have not been seen in the training period. A **quantile regression model** [75] is employed to predict suitable price guarantees given the household characteristics. For example, a single-family home equipped with a heat pump, built in the 1990s, with moderate insulation, a 5 kWp PV system, and a 10 kWh battery storage, no thermal storage, would have these characteristics fed into the quantile regression model. This was trained on the Monte Carlo-generated dataset and then predicts the aggregator's specific price guarantee for this household. We employ a quantile regression model due to its ability to extrapolate, its ability to consider varying risk preferences, and the interpretability of input factors [75].

Eventually, the suggested **household-specific price guarantees** are calculated for the evaluation period. The price guarantee suggestion can be seen as the real-world decision process of an aggregator under uncertainty (since exact future day-ahead prices, weather data, and setpoint profiles cannot be known). We then employ the home energy management optimization model for these exact years, using perfect knowledge of prices, weather, and setpoints. This allows us to conduct a **risk analysis** of the provided guarantees. We then compare the risk profiles of the outspoken price guarantees with those of a scenario where households remain subscribed to constant flat-rate electricity prices, and where no flexibility is provided. This comparison highlights the relative trade-offs in financial risk and operational benefits, providing aggregators with insights into whether transitioning households to dynamic tariffs with price guarantees is a more viable strategy than maintaining the status quo. Finally, the impact and hence feature importance of the **input variables** on the proposed guarantee is analyzed to investigate the main factors determining household-level electricity price guarantees. This can include household characteristics (e.g., building insulation, thermal and electrical storage capacity), preferences (e.g., allowed setpoint deviations), weather characteristics, and raw market characteristics (e.g., mean annual electricity price).

3.1. Home energy management system optimization model

The following section presents the mathematical formulation of the underlying home energy management system optimization model, building on state-of-the-art research in cost minimization modeling [73,78], building thermal dynamics [76], heat pump operations [26,86], thermal storage systems [31], and BESS integration [73]. The objective of the energy management system is to minimize household costs, considering time-varying spot market prices, household load, PV generation, and flexibility potential. Household load comprises the load of household appliances and the electricity demand induced by the heat pump. The flexibility potential is determined by a potential BESS installation, the operational flexibility of the heat pump and a backup heater (which is used when the heat pump's thermal power is insufficient), thermal building inertia, and the possible presence of thermal storage, as well as some potentially granted thermostat setpoint flexibility. The home energy management system operation is modeled in an hourly resolution, which is commonly used in the literature and corresponds to the previous hourly contract duration in the European day-ahead electricity market [78].

3.1.1. Objective function

The objective function of a given household seeks to minimize its yearly electricity costs $C^{Tot.}$ (Eq. (20)). These yearly costs are computed as the sum of the household's electricity consumption $E_t^{Tot.}$ multiplied by the electricity prices p_t^{spot}, minus the PV generation fed back to the grid $E_t^{PV,Ext.}$ multiplied by the feed-in tariff p_t^{FIT} at each time step t:

$$\min C^{Tot.} = \sum_t \left(E_t^{Tot.} \cdot p_t^{spot} - E_t^{PV,Ext.} \cdot p_t^{FIT} \right) \tag{1}$$

The optimization problem is subject to the following constraints that govern the physical and comfort requirements of the household:

$$E_t^{Tot.} = E_t^{HH} + E_t^{HP} + E_t^{HR} + \frac{1}{\eta^{BESS}} \cdot E_t^{BESS,Ch.} - \eta^{BESS} \cdot E_t^{BESS,Dch.} - E_t^{PV,Int.}, \tag{2}$$

$$E_t^{PV,Tot.} = E_t^{PV,Int.} + E_t^{PV,Ext.}, \tag{3}$$

$$E_t^{Tot.} \cdot E_t^{PV,Ext.} = 0, \tag{4}$$

$$E_t^{HH}, E_t^{HP}, E_t^{BESS,Ch.}, E_t^{BESS,Dch.}, E_t^{PV,Int.}, E_t^{PV,Ext.} \geq 0. \tag{5}$$

In Constraint (2), the total energy consumption is expressed as the sum of the non-flexible household load E_t^{HH}, the heat pump consumption E_t^{HP}, the backup heater consumption E_t^{HR}, and the BESS charging demand $E_t^{BESS,Ch.}$, minus the PV generation consumed internally ($E_t^{PV,Int.}$) and the discharged energy from the BESS ($E_t^{BESS,Dch.}$). The BESS inverter efficiency is represented by η^{BESS}. We note that the inflexible household load E_t^{HH} includes all household electricity consumption beyond the heat pump.

In Constraint (3), the total production of the PV installation is divided into consumed generation and the remainder that is fed into the grid, accounting for potential profits from feed-in tariffs. The mutual exclusivity Constraint (4) ensures that PV generation is only fed into the grid once the household's demand has been satisfied. Additionally, the non-negativity of all energy components is enforced in Constraint (5).

The optimization problem could be altered to account for alternative regulatory regimes, for instance, by compensating the PV feed-in with spot market prices or by allowing BESS to discharge into the grid. However, for the sake of conciseness, we stick to the regulatory environment typically used in feed-in tariff environments. Note that the electricity prices p_t^{spot} also include taxes and grid fees, which could be either flat or time-variable based on spot market prices.

3.1.2. Battery operation

The household BESS is operated under the following constraints:

$$E_t^{BESS,Ch.}, E_t^{BESS,Dch.} \leq P^{BESS,Max.} \cdot \Delta t, \tag{6}$$

$$E_{t+1}^{BESS} = E_t^{BESS} + E_t^{BESS,Ch.} - E_t^{BESS,Dch.}, \tag{7}$$

$$0 \leq E_t^{BESS} \leq E^{BESS,Max.}, \tag{8}$$

$$N^{cycles} \geq \frac{1}{2 \cdot E^{BESS,Max.}} \sum_{t=0}^{T} \left(E_t^{BESS,Ch.} + E_t^{BESS,Dch.} \right), \tag{9}$$

In Constraint (6), the energy charged to and from the BESS $E_t^{BESS,Ch.}$ and $E_t^{BESS,Dch.}$ is constrained by the maximum BESS power $P^{BESS,Max.}$

multiplied by the duration of a time step Δt. In Constraint (7), the energy stored in the battery E_{t+1}^{BESS} is updated as a result of charging and discharging operations and the previous state of charge. The stored energy is further restricted by the BESS energy capacity $E^{BESS,Max.}$, as described in Constraint (8). Notably, in cases where a household does not possess a BESS, $E^{BESS,Max.} = 0$, thereby prohibiting any charging or discharging operations. Finally, Constraint (9) restricts the number of annual full equivalent cycles of the BESS to prevent excessive usage and consequent degradation. This limitation reflects manufacturer specifications on the maximum allowable cycles per year, adherence to which is necessary to maintain the system's warranty [46].

3.1.3. Heat pump operation and thermal constraints

The operation of the household's heat pump is designed to maintain the thermal comfort of the inhabitants, defined by the manually selected thermostat setpoint T_t^{set} at each time step. We model the impact of heat pump-generated thermal energy on indoor temperature while considering outdoor temperatures, irradiance, and the building structure. To this end, we implement a 1R1C reduced-order thermal model, also referred to as an RC model [76,90]. These RC models simplify the thermal dynamics of buildings by using analogies of resistors (R) and capacitors (C) to represent heat transfer and the thermal storage capacity of building materials [90]. The specific RC values depend on the building's thermal properties, such as insulation, construction materials, window size, and window type. Alternative RC models with multiple resistances and capacitances exist, such as the 2R1C or 2R2C models, which capture more detailed thermal dynamics and offer slightly better accuracy [76]. However, we chose the 1R1C model because it leads to a convex optimization problem with linear differential equations [89], thereby offering a good trade-off between simplicity and accuracy.

The equations governing the indoor and outdoor temperatures in relation to external heat inputs and the building's structure, based on the discrete formulation of the 1R1C differential equation from Zhang et al. [95] are as follows:

$$T_t = T_{t-1} + \frac{1}{R^{ia} * C^i}(T_t^{out} - T_t) + \frac{Q_{t-1}^c + Q_{t-1}^i}{C^i} \tag{10}$$

In this equation, T_t represents the indoor air temperature at time t, T_t^{out} is the outdoor temperature, Q_t^c refers to the thermal energy provided by the controllable equipment (e.g., heat pump, backup heater, thermal storage), Q_t^i is the thermal energy from irradiance, R_{ia} is the thermal resistance between the building interior and envelope, and C_i represents the thermal capacitance of the indoor air.

The thermal input from irradiance, Q_t^i, is defined as:

$$Q_t^i = P_s A_i \tag{11}$$

where P_s is the solar irradiation and A_i is the effective window area for absorption of solar heat gains in internal air [76].

We couple the thermal energy generated by the heat pump and the electrical energy E_t^{HP} required for it in Eq. (12), based on the Coefficient of Performance (COP) of the heat pump:

$$Q_t^{HP} = COP_t \cdot E_t^{HP}, \quad E_t^{HP} \le E^{HP,Max.} \tag{12}$$

The COP is determined by the outdoor temperature T_t^{out} and is derived from Verhelst et al. [86], based on an air-to-water heat pump system connected to a residential floor heating system:

$$COP(T_t^{\text{out}}) = c_0 + c_1 T_t^{\text{out}} + c_2 T_{w,s} + c_3 (T_t^{\text{out}})^2 + c_4 T_{w,s}^2 + c_5 T_t^{\text{out}} T_{w,s} \tag{13}$$

The parameters c_0, c_1, c_2, c_3, c_4 and c_5 are based on Verhelst et al. [86]; the water supply temperature $T_{w,s}$ is set at 45 °C based on field measurements [26].

The total heating demand Q_t^c can be satisfied by the heat pump thermal load Q_t^{HP}, the load discharged from the thermal storage $Q_t^{St.,Dch.}$ and the backup heater load Q_t^{HR}. We model optional thermal storage installations (in the form of a buffer tank) by setting up an energy balance of the storage, as in Fischer et al. [31], neglecting storage losses to the room and assuming homogeneous temperature distribution within the tank:

$$Q_t^c = Q_t^{HP} + Q_t^{HR} + \eta^{St.} \cdot Q_t^{St.,Dch.} - \frac{1}{\eta^{St.}} \cdot Q_t^{St.,Ch.} \tag{14}$$

In this equation, the thermal demand Q_t is met by the heat pump generation Q_t^{HP} and the thermal energy discharged from the storage ($Q_t^{St.,Dch.}$), minus the energy charged into the storage ($Q_t^{St.,Ch.}$). The efficiency losses of the storage are represented by $\eta^{St.}$. The thermal load of the backup heating element, Q_t^{HR}, is equal to E_t^{HR}, as resistance heating operates with a $COP = 1$. We note that we only consider thermal demand for heating, which represents the largest thermal consumption in households [11] and ignore running hot water demand (as in Hedegaard et al. [39] and Le Dréau and Heiselberg [52]), which we leave for future research.

We limit the thermal charging and discharging rate to a maximum rate $Q^{Ch./Dch.,Max.}$, to model realistic and feasible operation speeds [29]:

$$Q_t^{St.,Dch.}, Q_t^{St.,Ch.} \le Q^{Ch./Dch.Max.} \tag{15}$$

To model the thermal energy stored in the tank, we track its current charge $Q_t^{St.}$ over time:

$$Q_{t+1}^{St.} = Q_t^{St.} + Q_t^{St.,Dch.} - Q_t^{St.,Ch.} \tag{16}$$

The maximum energy stored in the thermal storage is limited by the size of the storage $Q^{St.,Max.}$:

$$0 \le Q_t^{St.} \le Q^{St.,Max.} \tag{17}$$

Analogous to the BESS, $Q^{St.,Max.} = 0$ implies that no buffer tank is installed. Both the maximum thermal energy stored in the buffer tank and the maximum discharging power are derived from an experimental evaluation [29].

The indoor temperature T_t^{in} at time step t may deviate from the setpoint temperature T_t^{set}. This deviation is denoted as T_t^{Δ}, which is defined as:

$$T_t^{\Delta} = |T_t^{\text{in}} - T_t^{\text{set}}| \tag{18}$$

We use these deviations to calculate discomfort costs, which are then integrated into the household optimization problem based on Baeten et al. [9]. We implement discomfort costs in the optimization problem to incentivize an operation according to the setpoint profile set by the household. The discomfort cost $C_t^{\text{Discomfort}}$ is determined by the amount of deviation beyond a permissible flexibility range T^{Flex}. If the deviation T_t^{Δ} exceeds the allowed flexibility T^{Flex}, a discomfort cost is applied. Otherwise, the cost is zero:

$$C_t^{\text{Discomfort}} = \begin{cases} p^{\text{Discomfort}}(T_t^{\Delta} - T^{\text{Flex}}), & \text{if } T_t^{\Delta} > T^{\text{Flex}} \\ 0, & \text{otherwise} \end{cases} \tag{19}$$

The discomfort costs $p^{\text{Discomfort}}$ are set relatively high ($= 100 \frac{EUR}{K}$) to prioritize thermal comfort over cost savings.

The originally introduced objective function is complemented by the discomfort costs to achieve cost savings while maintaining thermal comfort for inhabitants [9]:

$$\min C^{Tot.} = \sum_t \left(E_t^{Tot.} \cdot p_t^{spot} - E_t^{PV,Ext.} \cdot p_t^{FIT} + C_t^{\text{Discomfort}} \right) \tag{20}$$

3.2. Monte Carlo simulation

We conduct a Monte Carlo simulation to generate possible cost outcomes (and hence cost guarantees) for a diverse dataset of household, market, and weather parameters, which we subsequently use to train an algorithm for predicting cost guarantees at the individual household level. The Monte Carlo method is widely used for estimating result distributions based on random input parameters and uncertain variables [19,37]. We employ a Monte Carlo simulation because an exhaustive simulation of all potential parameter combinations is too computationally expensive.[1]

We simulate multiple iterations of price guarantee calculations, as described in the mathematical formulation in Section 3.1, using randomly drawn input parameters detailed in Section 4. The generated dataset serves as input for price guarantee forecasting in Section 3.3, where the resulting distributions are analyzed to evaluate risks from the perspective of the aggregator. The sample size and the convergence of the Monte Carlo simulation are evaluated based on the Central Limit Theorem [92], which ensures the stability and reliability of the Monte Carlo simulation by approximating the sampling distribution of the mean as normal with an increasing sample size. Convergence is validated by monitoring the width of the 99% confidence interval for the target variable, which stabilizes when additional iterations no longer significantly impact the confidence interval.

3.3. Quantile regression-based guarantee prediction and benchmark methods

After generating the underlying sample of price guarantees for different household characteristics, prices, and weather years, we employ a quantile regression to build a price guarantee prediction model [75]. Quantile regression is a statistical method used to estimate specific percentiles (quantiles) of a target variable based on a set of independent variables. Unlike linear regression, which predicts the average relationship between variables, quantile regression focuses on different points of the distribution, such as the median or upper/lower percentiles. This makes it particularly useful for the prediction of the desired low-price guarantees, as it allows aggregators to tailor guarantees to different levels of risk tolerance by focusing on specific segments of the price distribution.

Quantile regression estimates the conditional quantile function by solving the following minimization problem [60]:

$$\min_{\boldsymbol{\beta}} \sum_{i=1}^{n} \rho_\tau \left(y_i - \mathbf{X}_i^\top \boldsymbol{\beta} \right), \tag{21}$$

where $y_i \in \mathbb{R}$ is the dependent variable for observation i (e.g., the guaranteed price p_i^g), $\mathbf{X}_i \in \mathbb{R}^p$ is the corresponding vector of p explanatory variables (e.g., household or system characteristics), and $\boldsymbol{\beta} \in \mathbb{R}^p$ is the vector of quantile-specific coefficients.

The function $\rho_\tau(\cdot)$, known as the quantile loss or check function, is defined as:

$$\rho_\tau(v) = v \cdot (\tau - \mathbb{I}(v < 0)), \quad 0 < \tau < 1, \tag{22}$$

where $\mathbb{I}(\cdot)$ is the indicator function that returns 1 if the condition is true and 0 otherwise. This asymmetric loss penalizes under-predictions and over-predictions differently, depending on the choice of quantile τ. Minimizing the expected value of $\rho_\tau(y - a)$ with respect to a yields the τ-th quantile of y.

The quantile regression formulation in Eq. (21) does not require distributional assumptions about the residuals (e.g., normality) and is robust to outliers [60]. In the context of price guarantee forecasting, this method allows aggregators to tune their offers based on risk preferences. Lower quantiles (e.g., $\tau = 0.1$) correspond to more aggressive guarantees with lower prices, exposing the aggregator to higher financial risk. Higher quantiles (e.g., $\tau = 0.9$) represent more conservative guarantees with higher prices, reducing risk but potentially limiting household appeal.

The prediction model for the guaranteed electricity price p_i^g for household i is expressed as:

$$p_i^g = \beta_0 + \sum_{j=1}^{p} \beta_j X_{ij} + \epsilon_i, \tag{23}$$

where β_0 is the intercept, β_j are the quantile-specific regression coefficients for predictors X_{ij}, and ϵ_i is the residual error.

We set $\tau = 0.5$ for a balanced aggregator risk profile and conduct an additional sensitivity analysis for alternative quantiles.

In our approach to calculating low-price guarantees, we use the quantile regression to forecast relative changes as percentage deviations from the yearly average electricity price rather than directly predicting an absolute guarantee. This method has proven more effective in preliminary experiments, as it focuses on the underlying relationships between the guarantees and the input features, rather than being influenced by the absolute magnitude of electricity prices. Hence, using the percentual deviations prevents us from overfitting during extreme price periods and makes the approach more robust. It is also more realistic as it allows suppliers to agree to year-ahead contracts rather than indefinite price-reduction guarantees. By transforming the predicted percentage deviations back into absolute guarantees using the average electricity price, we ensure that the model remains adaptable to varying market conditions. This approach reduces the risk of overfitting to specific price levels or anomalies in the training data, thereby enhancing the robustness of the model, especially in years characterized by high price volatility. It also improves the model's generalizability, as percentage deviations inherently normalize the data.

We evaluate the performance of the quantile regression-based household-level guarantees by benchmarking them against a baseline scenario. In this baseline scenario, households face a uniform retail rate from their utility or aggregator, providing only limited incentives to utilize demand flexibility such as avoiding high spot market prices or capitalizing on low ones. The uniform retail rate is determined as the volume-weighted wholesale market price, calculated using representative standard load profiles for the respective years [15,45]. This baseline provides a realistic reference point, as uniform retail rates are widely used in existing energy market structures, allowing for meaningful comparisons with the proposed guarantee model.

3.4. Risk evaluation and feature importance

We can evaluate the quality of the predicted guarantees by comparing them to the actual achievable profit guarantee (p_i^{g*}) in the evaluation years. The calculation of actual achievable guarantees is subject to information not available to the prediction algorithm, the aggregator or the household, e.g., the realization of thermostat setpoint profiles, detailed weather profiles, and actual day-ahead price curves.

When assuming that a household i has been granted a guarantee p_i^g, we compare the realized total household costs $C^{Tot.}$ with the guaranteed costs, considering the guaranteed rate. The resulting difference between guaranteed costs and actual costs is denoted as "household result" in the remainder of the study. The following metrics are applied to analyze the risk of the given low-price guarantees based on the distribution of household results:

- **Realized average electricity cost per unit:** This metric represents the annual electricity cost per unit of total household consumption, calculated using day-ahead market prices for grid-supplied electricity and setting this cost in relation to the overall electricity demand

[1] With 12 building types, 3 modernization states, 900 setpoint profiles, 4 PV sizes, 4 battery sizes, 4 cities, and 4 price years, the total number of combinations is $12 \cdot 3 \cdot 900 \cdot 4 \cdot 4 \cdot 4 \cdot 4 = 8{,}294{,}400$. At 28.2 s per run on average on an Apple M1 chip, this amounts to over 2.7 CPU years.

of the household. As such, it enables a meaningful comparison of procurement costs across households from the perspective of a utility or aggregator.

- **Mean household result:** The mean household result is calculated for each evaluation year by comparing the pre-determined guarantees granted to households with the actual costs accrued during the year. Based on Ackermann et al. [1], we interpret a mean result of 0 as indicating that the guarantee-giving entity breaks even, neither incurring losses nor generating profits from the guarantee arrangement. This ensures that the guarantees align closely with the actual household costs, maintaining fairness and financial sustainability while reinforcing the reliability of the prediction algorithm.
- **Width of Distribution:** We evaluate the accuracy of the household result distributions by calculating the width of the 5%-95% confidence interval. The width of a distribution is a key metric for assessing variability and reliability [82]. In our case, narrower distributions of household results, reflected by a smaller width of the confidence interval, would indicate improved predictability and consistency in the outcomes of the guarantee framework. This makes width a particularly suitable metric, as it directly captures the deviation of the forecast from the actual result. The aggregator can ensure a reduced financial risk exposure by minimizing the width of this confidence interval.

We evaluate the factors influencing potential low-price guarantees by examining the effect size, direction, and significance of the coefficients in an ordinary least squares linear regression, using the relative difference between the guarantees and the average electricity price for the respective years as the target variable.

4. Model parameterization

In this section, we describe the parameters and distributions we use in the Monte Carlo simulation. We base our simulations on empirical price, weather and building data from Germany and solve the underlying household optimization problems in hourly resolution with the widely used Gurobi solver [36].

4.1. Building models

We model the building thermodynamics of the investigated households using reduced-order 1R1C thermal response models, which consolidate the thermal properties of buildings into a single thermal resistance (R) and capacitance (C) network. This approach provides a computationally efficient and accurate representation of thermal dynamics [76]. The input for these models is derived from representative German building typologies, encompassing various construction periods and insulation states. These typologies were developed as part of a large-scale statistical analysis of the European (and specifically German) building stock [10].

The dataset includes 12 distinct building types (as shown in Table 1) and three modernization variants: original condition, conventional renovation with moderate insulation, and deep renovation with high insulation. We utilize the 1R1C values computed in Sperber et al. [76], along with the distribution of building sizes and living areas, which are subsequently used to determine appropriate heat pump sizes as follows.

Table 1
Summary of single-family house (SFH) typologies with construction periods, heated living areas, building stocks, and corresponding parameters A_i, C_i, and R_{ia} from Sperber et al. [76], for the building stock at the end of 2018.

Code of building type	Construction period	Heated living area in m^2	Building stock (in thousands)	A_i	C_i	R_{ia}
SFH A	< 1859	199	330	1.45	3.17	4.76
SFH B	1860–1918	129	966	1.12	2.74	6.08
SFH C	1919–1948	275	1131	2.89	3.82	3.35
SFH D	1949–1957	101	859	0.92	2.10	7.51
SFH E	1958–1968	110	1509	1.36	2.72	5.57
SFH F	1969–1978	158	1507	1.71	3.33	5.27
SFH G	1979–1983	169	704	1.35	2.67	6.22
SFH H	1984–1994	137	1160	1.75	2.88	6.19
SFH I	1995–2001	111	1035	2.00	2.09	7.31
SFH J	2002–2009	133	907	5.11	8.00	7.35
SFH K	2010–2015	160	494	5.61	8.00	6.59
SFH L	> 2016	160	258	5.72	8.00	6.71

4.2. Heat pumps and thermal storage

We derive the size of the heat pump from the living area of the investigated building types presented in Table 1. We follow an established sizing rule [33], which recommends a nominal heat pump power of 69.8 W/m^2 for non-retrofitted buildings, across all building types, including retrofitted ones. This conservative approach ensures sufficient capacity for peak heating demands and simplifies the simulation process. Additionally, we assume that every household is equipped with a 6kW backup heater [21]. The heat pump COP is calculated based on field measurements from an air-to-water heat pump with a water supply temperature of 45 °C, fitted to a polynomial function of the outside temperature [26]. Detailed parameters for this calculation are provided in the Supplementary Material (see Table A.4).

We also model the potential inclusion of a thermal storage installation. We assume that a 0.5m^3 (500l) thermal storage water tank provides 17.8 kWh of thermal flexibility potential, which can be fully discharged in one hour [29]. Currently, there is no empirical data on the prevalence and distribution of thermal storage in heat pump-equipped households. Therefore, we assume that 50% of such households are equipped with additional heat storage, with half of these having a small 500-liter tank and the other half a large 1000-liter tank. This assumption aligns with product variants offered by major heat pump and water storage manufacturers [81].

4.3. Thermostat setpoints

The thermostat settings of the investigated households represent a source of flexibility but also uncertainty for aggregators. To address this, we utilize 1000 empirical yearly setpoint profiles from [20], measured in 2017. We use 80% of these profiles during the Monte Carlo simulation, reserving the remaining 20% for the evaluation period. This approach ensures that the setpoint profiles of the households in the evaluation period are unseen during training, thereby reflecting the decision-making challenges and uncertainties that aggregators would encounter in practice. It should be noted that the setpoint dataset from Luo and Hong [20] is based on a US sample, which may exhibit heating patterns differing from those typical in other countries. However, there is no comparable dataset available.

Additionally, we model the option for households to adopt a nighttime setback feature, in which the thermostat temperature is reduced to 15.6 °C between 10 PM and 6 AM, as described in Moon and Han [61]. This feature is incorporated to evaluate whether offering such a contract option affects the possible low-price guarantees. We assume that 75% of households opt for unobstructed thermostat operation, corresponding to a “heating-as-desired” scenario. This reflects findings from studies such as Sachs et al. [71], which indicate that most users prioritize maintaining thermal comfort over energy-saving behaviors, with many overriding energy-saving thermostat settings or avoiding setback options entirely. Furthermore, we assume that all households may offer 0 °C, 1 °C, or 2 °C setpoint flexibility as a contract detail (i.e., allowing the operator to deviate from the desired setpoint), with these values being equally probable for the Monte Carlo simulation. This contracted flexibility introduces the potential for gaming (e.g., offering a 2 °C flexibility potential and subsequently increasing the daily setpoint profile by 2 °C). Designing corresponding incentive systems to ensure the revelation of correct underlying preferences remains a subject of future research.

4.4. PV and BESS

We derive the distribution of PV installations and BESS sizes from empirical data of a German governmental registry of energy-related installations [57], which we parsed and processed using the *open-mastr* package [50]. In our analysis, we focus on PV systems with a nominal power of 10kW or below and BESS systems with a capacity of 10 kWh or less, which we consider representative of typical household sizes [38]. This excludes large-scale and industrial storage installations, which are beyond the scope of this study. As of December 12th, 2024, there were 1,672,942 BESS installations and 3,210,749 PV systems recorded within the set range.

We assume all simulated households to be equipped with a PV system, as we consider this a viable future scenario for those households that might provide demand-side flexibility given the rapidly increasing number of PV installations [23]. Since larger PV systems are typically associated with larger battery storage capacities, we do not assume independent distributions for PV sizes and BESS capacities in our Monte Carlo simulation. Instead, we define four PV size buckets (0.1–2.5kW, 2.5–5kW, 5–7.5kW, 7.5–10kW) and five BESS capacity buckets (0 kWh [no storage], 0.1–2.5 kWh, 2.5–5 kWh, 5–7.5 kWh, 7.5–10 kWh). The resulting distributions are shown in Fig. A.12 in the Supplementary Material.

An analysis of this data shows that larger PV installations tend to correlate with larger storage systems, while smaller PV systems are predominantly paired with smaller or no BESS. In our Monte Carlo simulation, the PV size for each household is first drawn from the defined PV size buckets based on their assigned probabilities. Subsequently, the BESS size is drawn from the corresponding BESS capacity bucket associated with the selected PV size bucket. This conditional sampling approach reflects the observed real-world relationship between PV and BESS sizes, providing a more realistic representation of household configurations in the simulation.

Based on the drawn PV sizes, hourly PV generation time series are created following the widely-proliferated method from Pfenninger and Staffell [68], incorporating variations in cloudiness, irradiance, and other weather factors, while assuming a 10% system loss, 35 ° tilt, and 180 ° azimuth. However, real-world panels vary in azimuth, tilt, and efficiency. For the sake of conciseness, we consider one uniform system. The allowed BESS Equivalent Full Cycles (N^{cycles}) are set at 365, representing one cycle per day. The maximum discharge power $P^{BESS,Max}$ is calculated by multiplying the sampled BESS size by 0.41, based on German field measurements [73].

4.5. Day-ahead prices and grid fees

The dynamic tariffs in our study are based on the day-ahead market price of the German market zone in the European electricity market, obtained from Bundesnetzagentur [14]. We chose the German-Luxembourg market zone as it is the largest and most liquid market zone within the European market. We depict the observed prices in Fig. 3, showing high price fluctuations from 2021 onwards. The years 2021, 2022, and 2023 are then used as evaluation periods to assess the model's performance even under challenging market conditions characterized by high price volatility. Testing the model in such an environment is essential to assess its robustness and adaptability, ensuring it can effectively handle extreme fluctuations and provide reliable outcomes even under highly dynamic and uncertain market scenarios.

In addition, we consider grid charges, as well as taxes and levies from [22] in our study, to model household electricity costs realistically. We use yearly average electricity prices as input for the quantile regression, as described in Section 3.3. The resulting grid charges, taxes, levies, average market prices, and volume-weighted average prices are shown in Table A.5 in the Supplementary Material.

4.6. Weather data

The underlying thermal building model is influenced by two weather variables: the solar irradiance and outside temperature [76]. We obtain weather data for four German cities, Munich, Cologne, Berlin, and Potsdam [87,93], to model the impact of different weather patterns and associated temperature differences. We use weather data from the same days as the day-ahead prices.

Fig. 4 shows the temperature and Global Horizontal Irradiance (GHI) over the target cities and investigated years. We observe the same pattern across all cities (lower temperatures and irradiance in winter, higher values in the summer), with some regional differences. For instance, Munich consistently exhibits lower irradiance, while temperatures tend to be higher in Cologne.

The RC values in Sperber et al. [76] are fitted based on Southern Vertical Irradiance instead of the more common Global Horizontal Irradiance. Hence, we transform the GHI values in an additional step to Southern Vertical Irradiance with the Python package *pvlib* [41]. We depict the resulting change in the irradiance curve in the Supplementary Material in Fig. A.13.

5. Results

The results are divided into three parts: First, we validate the outcomes of our home energy management optimization and thermal models by comparing the simulated household electricity and thermal energy demand to official German statistics. Second, we analyze the economic value of aggregators controlling the flexibility potential of households. Third, we examine the resulting low-price guarantees and the associated risks for aggregators. Finally, we investigate the feature importance for guaranteed prices.

5.1. Home energy management system validation

We optimize the household operation based on the model from Section 3. With fixed guaranteed prices, households would not be incentivized to shift demand, but the aggregator would be exposed to dynamic price risk. To manage the risk, the aggregator actively utilizes household flexibility, which may involve optimizing battery and thermal storage operations or adjusting building (pre-)heating schedules. These actions are performed within the boundaries of user-defined comfort constraints.

In Figs. 5–7, we compare the way the home energy management system operates based on different flexibility provisions on the same day for the same household (a single-family home (SFH A) that has been renovated, an 8.75kW PV installation, 8.75Wh BESS, 1000-liter thermal storage buffer tank, 1 °C of granted setpoint flexibility, in Berlin on the 20th of January, 2022).

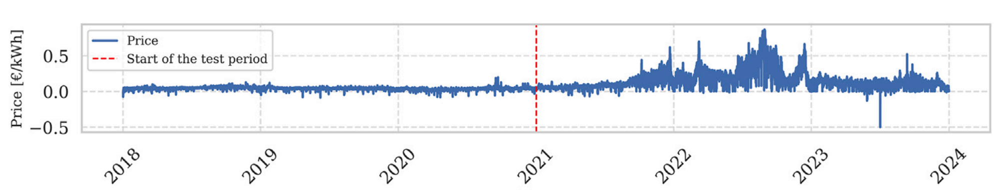


Fig. 3. Mean daily day-ahead spot market prices for the DE/LU market zone, obtained from Bundesnetzagentur [14].

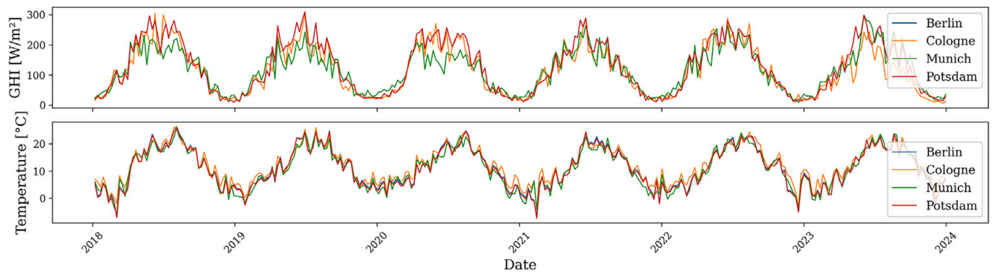
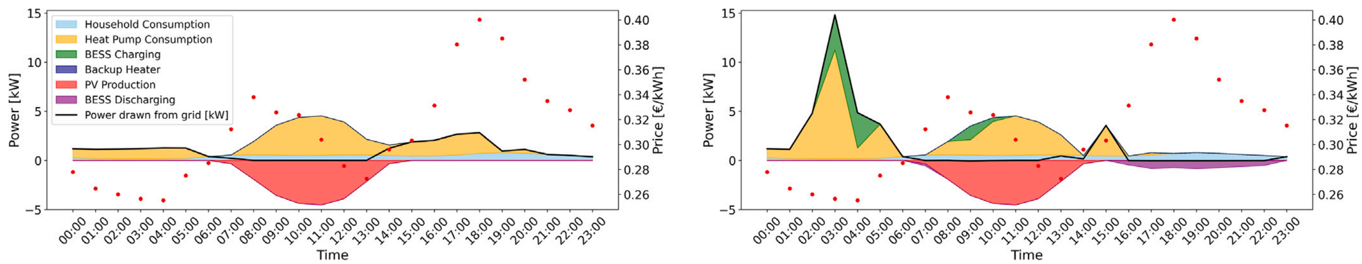
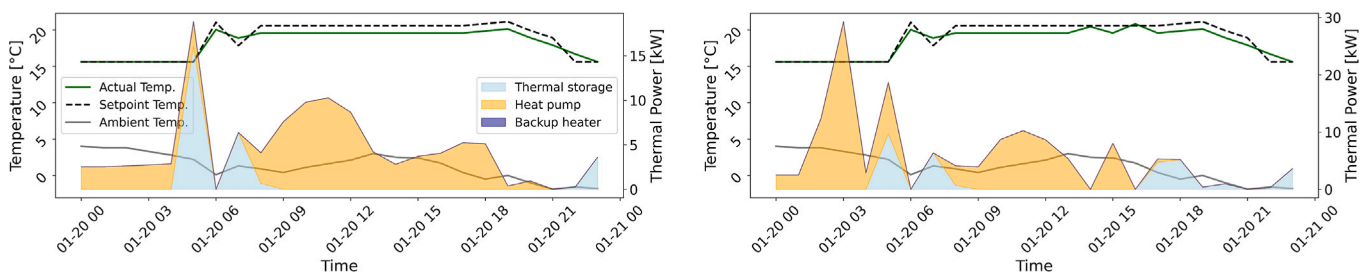


Fig. 4. Mean weekly temperatures and solar irradiation (GHI) in the four investigated cities, obtained from Visual Crossing [87].



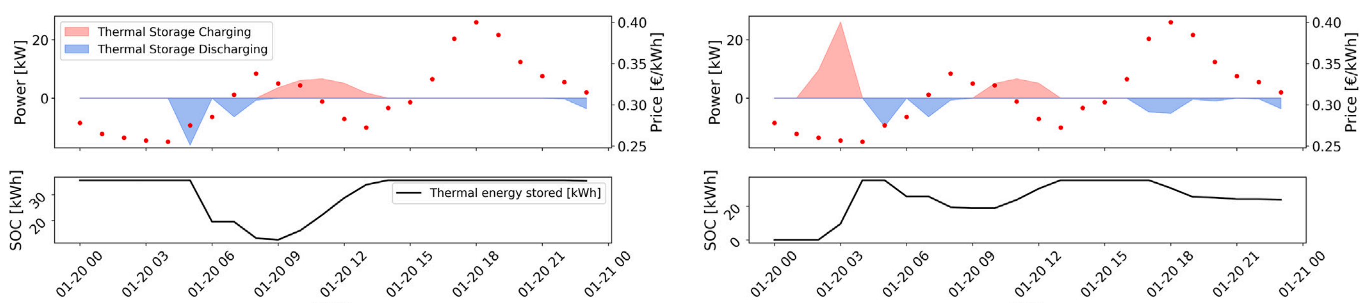
(a) Household controls flexibility (b) Aggregator controls flexibility

Fig. 5. Electrical energy balance. Day-ahead price in red dots.



(a) Household controls flexibility (b) Aggregator controls flexibility

Fig. 6. Thermal model.

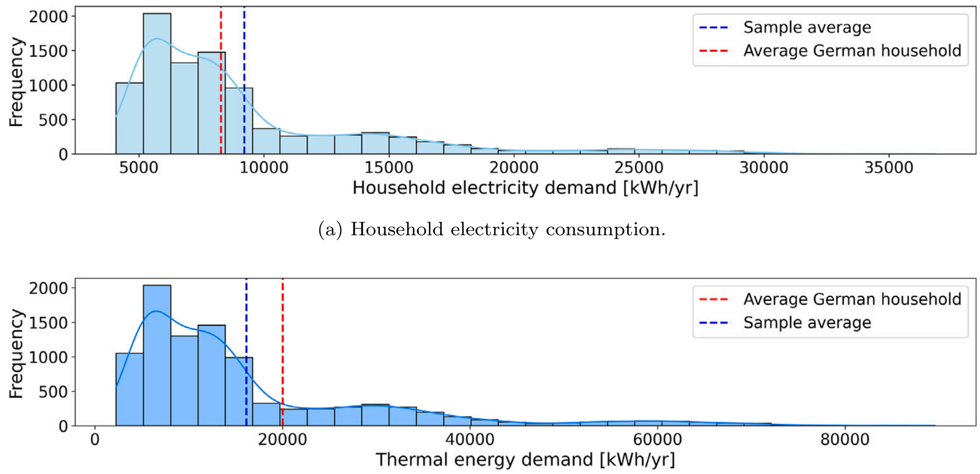


(a) Household controls flexibility (b) Aggregator controls flexibility

Fig. 7. Thermal storage operation.

Fig. 5(a) illustrates the electrical energy balance of the household, comparing demand components (heat pump, backup heater, household consumption, BESS charging) and supply components (PV production, BESS discharging) alongside the day-ahead market prices for the given day. The resulting power drawn from the grid is depicted as a solid black line. In the case of the home energy management system controlling its flexibility potential, the household primarily focuses on maximizing self-consumption during the PV generation peak around noon. However, during the evening price peak, the household remains unaffected by price fluctuations, leading to most of the power being drawn from the grid. Conversely, in the aggregator flexibility scenario, the flexibility potential is utilized to minimize power draw from the grid during the evening price peak (Fig. 5(b)). In this case, heat pump loads are shifted forward temporally, and the BESS is discharged during peak price times, having been charged during the low-price period at night.

We present the outcomes of the thermal building model in Fig. 6(a), which shows the desired setpoint temperature (dotted grey line), the actual indoor temperature (green line), the ambient temperature (solid



(a) Household electricity consumption.

(b) Thermal energy Demand

Fig. 8. Histogram of yearly household electricity consumption and thermal demand of the whole sample.

grey line), and the thermal energy provided by the heat pump and the discharge of the thermal storage. In both scenarios, the heat pump operates in the morning to accommodate a setpoint temperature increase. Later in the day, the heat pump activates earlier than in the case where the aggregator has no control over the household flexibility, and the thermal storage is discharged to mitigate the evening price peak (Fig. 6(b)). The granted 1 °C setpoint flexibility is employed to pre-heat the building during low-price periods, allowing the indoor temperature to decline during peak-price hours, effectively using the building as thermal storage.

Fig. 7(b) also displays the operation of the thermal storage. We can observe that in the dynamic case, the thermal storage is charged during the night at lower prices.

We proceed to evaluate the household electricity and thermal energy demand across the sample obtained after 9404 iterations of the Monte Carlo simulation that is depicted in Fig. 8. We have analyzed the convergence of the Monte Carlo simulation according to the Central Limit Theorem, as described in Section 3.2. After 2805 runs, convergence based on a 99% confidence interval has been reached, as depicted in Fig. A.14 in the Supplementary Material. These results are compared with German average values. We assume a benchmark average household electricity consumption of 3383 kWh, based on official German statistics from Destatis [25] and an average annual heat pump electrical consumption of 34.5 kWh/m^2, based on manufacturer estimates [17]. For thermal energy demand, we assume an average of 130 W/m^2, as reported in Destatis [24], which is then multiplied by the average area of the investigated households (153 m^2). The average household electricity consumption in the sample is close to the calculated German average values. Also, the average thermal energy demand aligns closely with the German average. For both household electricity consumption and thermal energy demand, we observe long-tailed distributions with significant outliers. These outliers are predominantly associated with poorly insulated buildings, leading to disproportionately high heat demand, consistent with findings from existing research [3].

The analysis conducted in this section evaluates the accuracy of the simulation framework and modeling of the home energy management system by comparing the resulting electricity demand to national statistics, ensuring the model's reliability, which is required for the design of robust low-price guarantees.

5.2. Value of aggregator control over household flexibility

In this section, we evaluate the benefits of the aggregator managing household flexibility by comparing the average electricity prices achieved under two scenarios: one where the home energy management system operates based on constant electricity prices, and another where the aggregator controls flexibility using dynamic market prices. We note that the "aggregator controls flexibility" scenario is equivalent to one where the household opts for a dynamic tariff-oriented control on its own. However, considering the aversion of households towards dynamic tariffs, we consistently denote this case as the "aggregator controls flexibility" case.

In Fig. 9 (and in Table A.8 in the Supplementary Material), the distribution of realized yearly electricity prices over all households in the sample is depicted, demonstrating the clear economic benefits of the aggregator managing household flexibility under dynamic prices. Across all years, the aggregator's control consistently leads to lower mean average electricity prices compared to a scenario where the home energy management system relies on constant prices and is optimized to increase self-generated PV power consumption. The most significant relative reduction occurs in 2022, with an 8.48% (3.4ct) lower mean electricity price, reflecting the value of adapting to dynamic market prices during a volatile period.

While the absolute reductions in prices vary by year, they consistently translate into meaningful percentage decreases, emphasizing the aggregator's ability to utilize flexibility to optimize costs. On average, over all years analyzed, the aggregator reduces electricity prices by 7.36% (2.5ct), underlining the consistent value of dynamic control across varying market conditions.

In addition, we observe that under aggregator control, the majority of households achieved electricity prices below the volume-weighted average electricity price, which can be interpreted as a competitive retail rate. Specifically, 78.40% of households realized a lower price per unit of electricity consumed through dynamic control, compared to only 32.67% in the baseline scenario.

While we show the economic benefit of the dynamic tariff-oriented operation of household flexibility potentials, the observation has been made ex-post. However, since we want to reduce the price risk for households while controlling the risk for aggregators, we aim to suggest household-specific cost guarantees even before we know the exact realizations of prices, weather, and behavior, with which we proceed in the following section.

5.3. Price guarantee risk evaluation

To overcome the loss aversion of households, we suggest that aggregators offer fixed tariffs with low-price guarantees. This section is dedicated to evaluating the associated risks of these guarantees for aggregators.

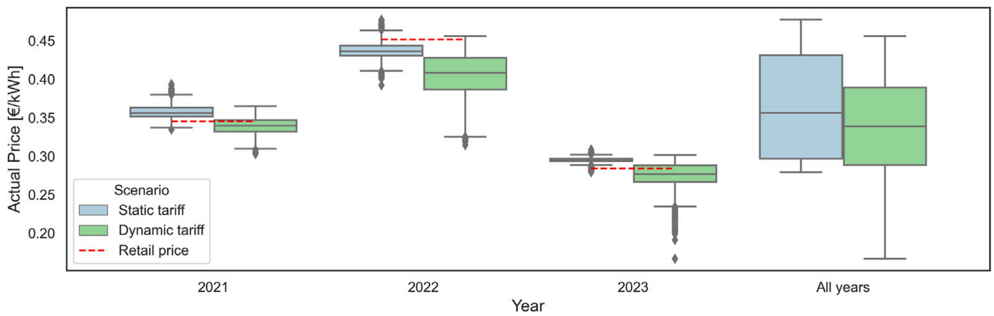


Fig. 9. Actual costs per unit of consumed electricity per household, under static and dynamic tariffs. Volume-weighted average electricity prices are shown in red dotted lines (including fees, taxes, and grid charges).

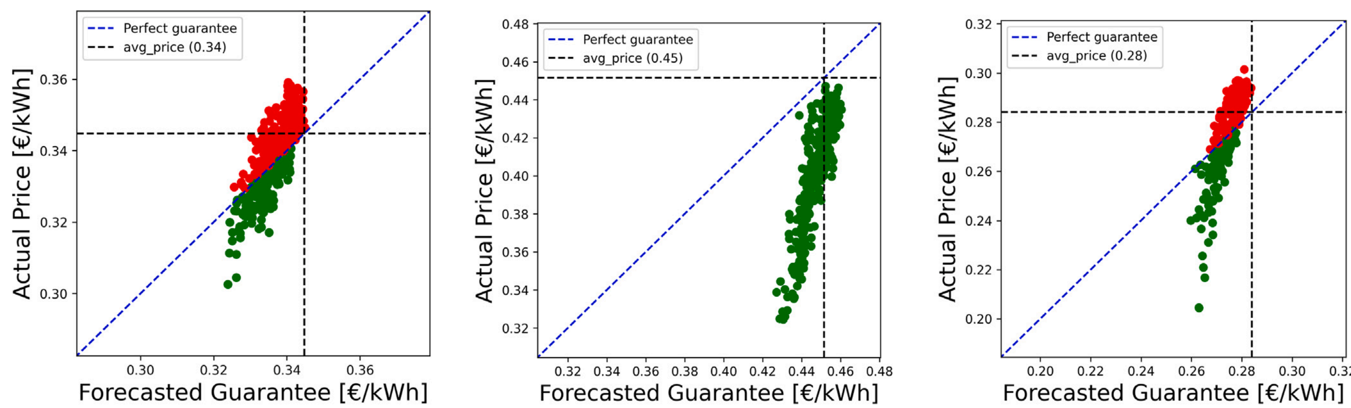


Fig. 10. Comparison of guaranteed and realized prices per household. The blue line represents a perfect prediction (predicted costs = actual costs). The grey dotted lines represent the volume-weighted yearly average electricity price. Red dots represent a loss for the aggregator (guaranteed prices < actual prices), and green dots represent a profit (guaranteed prices > actual prices).

We use the previously described Monte Carlo sample to train our quantile regression-based guarantee prediction model, which is then used to forecast guarantees on a household basis for the previously unseen years 2021, 2022, and 2023. We calculate household results based on the approach described in Section 3.4. We assume that a certain electricity price has been granted to the household (either as a usual flat household tariff or in the context of a guaranteed lower price in exchange for the right to control the household's flexibility potential). Then, we calculate costs (or profits) that occur on a household basis for the aggregator. We analyze the distributions of household results (the difference between costs that were guaranteed and the ones that actually accrued) to evaluate the associated risks.

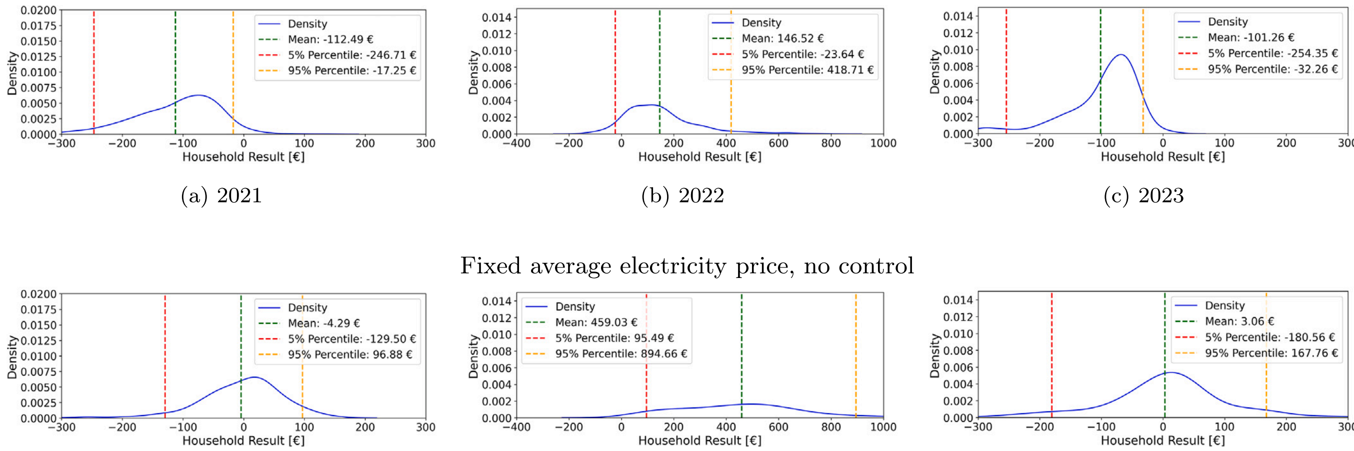
5.3.1. Realized average electricity cost per unit

Fig. 10 illustrates the household-level guarantees for each year of the study. In an ideal scenario with perfect predictions, these guarantees would align precisely with the actual achievable electricity prices, as represented by the blue angle bisector. However, due to the inherent uncertainties in thermostat setpoints, weather, irradiance, PV output, and realized electricity prices, deviations between the predicted guarantees and the actual prices are evident. This discrepancy is especially noticeable in 2022, where the forecasted guarantees consistently exceeded the actual household electricity costs. The primary reason for this is the price dynamics shown in Fig. 3. During 2022, there were significant price spikes in the summer months. However, the guarantee prediction algorithm is based on average annual electricity prices that, in previous training years, mainly had elevated price levels in winter. Since 2022's price spikes occurred during summer, when the simulated households had PV production to offset costs, the algorithm overestimated the guarantees.

Overall, the quantile regression demonstrates an ability to capture the relationship between individual household-level guarantees and realized costs. Households with lower guarantees generally exhibit lower realized prices, while those with higher guarantees tend to align with higher realized costs. This finding is significant, as it indicates that even under the inherent uncertainty of weather patterns, price dynamics, and individual heating behavior, it is possible to formulate meaningful guarantees using only household characteristics and aggregated price and weather statistics. Furthermore, as already highlighted in Fig. 9, most households achieve actual electricity costs below the volume-weighted average electricity price, commonly viewed as a competitive retail rate. This reinforces the earlier observation that these households would have realized financial benefits by adopting a dynamic tariff or guarantee structure.

However, while the majority of households benefit from guarantees and the dynamic control of their flexibility potential, some households experience guarantees and realized prices that exceed the competitive retail rate. This can occur, for example, when a household's heating demand often aligns with price peaks or when the building's limited thermal inertia restricts its thermal flexibility.

In addition, a comparison of standard deviations shows that the suggested guarantees are substantially less volatile than the actual realized costs. For example, in 2023, the standard deviation of forecasted guarantees amounted to 0.0049 €/kWh, compared to 0.0160 €/kWh for realized household costs. If households had subscribed to regular dynamic tariffs, the higher volatility of realized costs would have exposed



(a) 2021 (b) 2022 (c) 2023

Fixed average electricity price, no control

(d) 2021 (e) 2022 (f) 2023

Individual guarantees, with control

Fig. 11. Distributions of household results from the aggregator's perspective for different cases and years.

them to greater risks and potential disutility. In contrast, the guarantees exhibit a narrower spread across households and would have provided predictable fixed reduced prices in return for granting their flexibility potential.

5.3.2. Mean household result

In Fig. 11 and Table 2, the resulting distributions of profit (or loss) per household from the aggregator's perspective are depicted for the benchmark- and guarantee-case. A desirable distribution of household results is characterized by a mean close to zero, indicating that the aggregator has accurately predicted guarantee values and has a balanced portfolio [1]. A mean household result close to zero ensures that aggregators neither incur excessive losses nor achieve disproportionate gains. A mean close to zero also suggests that the guarantees align well with actual household costs, reflecting the algorithm's capacity to account for diverse variables such as weather fluctuations, household consumption patterns, and market price dynamics. Additionally, we assess the width of the confidence interval of the distribution.

In two of the three years analyzed, the mean household results are significantly closer to zero when the aggregator provides individual guarantees and manages the flexibility potential. This demonstrates that offering guarantees leads to a more accurate alignment with actual household costs while maintaining a balanced portfolio, where losses from some households are offset by profits from others. However, 2022 stands out as an outlier again due to summer price spikes and overly conservative price guarantees, resulting in financial gains for the aggregator in that year.

5.3.3. Width of confidence interval

In all three years, household-level guarantees resulted in higher mean outcomes for the aggregator compared to scenarios without control over flexibility potential. This suggests that guarantee contracts can provide mutual benefits: households gain access to lower prices than the retail rate without compromising comfort, while aggregators enhance their financial performance. However, this improvement comes with a trade-off in the form of a wider confidence interval of financial results, reflecting greater variability. For example, in 2022, the baseline case showed a 90% confidence interval ranging from −23.64 to 418.71 €, whereas for the individual guarantees, the interval extended from 95.49 to 894.66 €.

Table 2
Results per case and target year.

Case	Target year	Mean	Interval width
Fixed average electricity price, no control	2021	−112.49	229.46
Individual guarantees, with control	2021	−4.29	226.37
Fixed average electricity price, no control	2022	146.52	442.36
Individual guarantees, with control	2022	459.03	799.16
Fixed average electricity price, no control	2023	−101.17	221.13
Individual guarantees, with control	2023	3.06	348.33

5.4. Feature importance of input factors

In this section, we focus on the input factors influencing guarantee levels. This is done through a linear regression analysis that links household characteristics and endowments to the difference between the guarantees and the average electricity price for the respective years.

The regression results in Table 3 provide valuable insights into the key drivers of guarantee level suggestions. The model includes household characteristics such as building type and modernization status,[2] flexibility endowments including thermal storage capacity (*E_s_max*) and battery storage capacity (*E_bess_max*), PV system size, weather conditions (*weather_avg*), granted setpoint flexibility, and the option for nighttime setback. From an operational standpoint, these insights could inform the development of a decision support system for aggregators, enabling real-time guarantee suggestions tailored to customers based on these observable household characteristics.

The R-squared value of 0.484 indicates that the model explains 48.4% of the variance in the relative difference between the guarantees and the average electricity price, suggesting moderate predictive power.

[2] We have opted to model modernization status as a continuous variable in the regression model to simplify the analysis and allow for an approximate interpretation of its influence on the relative difference between the guaranteed and average price. However, this approach assumes a linear relationship between modernization status and the target variable, which may not fully capture the distinct effects of each discrete category (1, 2, 3).

Table 3
Summary of the OLS regression results, explaining the impact of household characteristics on guarantee levels, in relative differences to the average electricity price in the investigated years. Significance levels: *p<0.05, **p<0.01, ***p<0.001.

Dep. Variable:	Relative Difference Guaranteed to Avg. Price [%]			R-squared:		0.484
Model:		OLS		Adj. R-squared:		0.483
F-statistic:		551.0		Prob (F-statistic):		0.00
BIC:		2.917e+04		AIC:		2.911e+04
	coef	std err	t	P> $\|t\|$	[0.025	0.975]
const	30.9576	1.014	30.532	0.000***	28.970	32.945
building_type	−0.1691	0.022	−7.537	0.000***	−0.213	−0.125
Modernization Status	−1.0983	0.094	−11.716	0.000***	−1.282	−0.915
E_s_max	−0.1721	0.005	−32.879	0.000***	−0.182	−0.162
E_bess_max	−1.1545	0.025	−46.742	0.000***	−1.203	−1.106
sampled_pv_size	0.1585	0.028	5.723	0.000***	0.104	0.213
weather_avg	−2.5502	0.088	−29.011	0.000***	−2.722	−2.378
flexibility	−0.6179	0.094	−6.556	0.000***	−0.803	−0.433
setpoint_option_nighttime_setback	0.3495	0.178	1.958	0.050*	−0.000	0.699

While the model captures key drivers, half of the variance remains unexplained, which is expected given that the model lacks information about actual household behavior and the exact weather and price curves in the respective years.

We note that all variables except the option to opt for the nighttime setback are significant at a 0.1% level, indicating that each contributes meaningfully to explaining the variance, and their inclusion strengthens the reliability of the model. This finding has operational implications for the aggregator, as it guides the selection of relevant customer information to request before offering household-level low-price guarantees, ensuring a more focused and effective decision-making process.

The coefficients of the independent variables in the regression illustrate how a one-unit increase in a given characteristic translates into a percentage point change in the relative difference between the guaranteed price and the average electricity price. For example, an increase in modernization status or newer building types is associated with lower prices. This underscores the significant role of thermal building dynamics in flexibility modeling. Modernized buildings, with improved insulation and thermal properties, function as more effective thermal mass storage, enabling greater savings from demand-side flexibility.

The coefficient for PV size demonstrates a counterintuitive effect. This arises from the focus on modeling the relative difference in guarantees rather than absolute costs. While PV installations reduce overall energy consumption and household electricity costs, they do not enhance flexibility potential. Instead, they primarily reduce grid electricity usage during high feed-in periods, which often align with low spot market prices. A similar rationale applies to the effect of the nighttime setpoint setback option (which is only significant at a 5% level). Although this option can lower heating demand and reduce electricity bills, it does not add to the household's flexibility potential and thus has a limited impact on the guaranteed price reduction.

6. Discussion

Uncertainty is a major obstacle to the widespread adoption of dynamic tariffs [77]: households are discouraged by the risk of unpredictable price fluctuations, while aggregators avoid offering guaranteed reduced flat tariffs due to the difficulty of accurately modeling household flexibility across electrical, thermal, and behavioral dimensions. Our study addresses these challenges by demonstrating that the market-oriented management of household flexibility, such as through an aggregator, can generate substantial savings for households while being profitable for the aggregator.

Our findings align with previous studies that highlight the economic value of household flexibility potential, but we take a different approach regarding how this flexibility should be utilized in the market. While earlier research often assumes households will eventually adopt dynamic tariffs independently, we advocate for transferring the management of their flexibility and associated price risk to aggregators in exchange for fixed low-price guarantees. In this context, household flexibility potential can be viewed as a tradable good. Our study provides valuable insights into how this tradable good can be priced under uncertainty, based on the suggested quantile regression-based decision support system. Our approach acknowledges that the flexibility potential of households can vary, and thereby have different economic potentials for households and aggregators that agree to take over the flexibility management. A special emphasis of our study, compared to related work, lies in the modeling and consideration of the thermal inertia of buildings, based on their construction year and modernization status. This leads, again, to varying flexibility potentials for heat pump operation: a household living in a well-insulated, modern building could shift heating demand more easily, and hence receive a better price guarantee from the aggregator.

We observed that the financial mean household result for the aggregator is consistently higher than the baseline status quo and close to zero in two of the three years analyzed. The first observation underlines the financial incentives for aggregators to provide guarantees, while the second highlights the portfolio-balancing effects of aggregator control. Under regular dynamic tariffs, some households may benefit while others incur losses, which can discourage participation. By contrast, the proposed low-price guarantees ensure that all households benefit from reduced rates in exchange for granting control over their flexibility potential. Although aggregators may experience losses with some households, these are offset by gains with others, creating a balanced portfolio. This risk transfer to professional aggregators strengthens the case for the guarantee concept and mirrors practices in the financial sector, where peer-to-peer lenders shift risks to experienced guarantors [88].

We note that our study has certain limitations. Only four geographical locations were considered, and a uniform heat pump type and COP were assumed. Further, the PV systems are modeled with the same tilt, azimuth, and system efficiency. The thermal building dynamics are represented with a simplified 1R1C model, which facilitates tractability but might not fully capture building behavior. Household heating setpoints were sampled from U.S. data due to a lack of data availability, which may not fully reflect European usage patterns. Additionally, assumptions had to be made about the prevalence and size of thermal storage, as such data points are not publicly available. Nonetheless, we see the selected input parameters and modeling assumptions as a valid overall representation of households with different heating profiles, building types, and flexibility endowments.

7. Conclusion, outlook and future work

In this section, we conclude our study with a summary of our findings and a perspective on the technical and regulatory requirements necessary to implement the proposed concept of household-individual price guarantees in practice, as well as an outlook on relevant future work.

7.1. Conclusion

Our study proposes an approach for promoting the adoption of dynamic electricity tariffs among households by reducing the associated cost uncertainty. Households are given low-price guarantees in return for control of their flexibility potential from battery storage systems, thermal storage systems, and their buildings' thermal inertia. Price risks are transferred from households to aggregators, who control the flexibility.

To show the viability of our proposal, we perform a three-stage process to formulate household-specific price reduction guarantees based on a combination of deterministic and stochastic simulations. The guarantees account for household characteristics such as building insulation, energy storage capacity, and thermal flexibility. Using quantile regression, we show that aggregators can predict price guarantees profitably ex-ante while being exposed to uncertainties in market prices, weather conditions, and household behavior.

The proposed low-price guarantees reduce households' risk, while they enable aggregators to optimize the use of household flexibility potential. This contributes to an overall market balance. By capitalizing on this flexibility potential, aggregators can reduce their resulting exposure to peak electricity prices. Our results show the potential beneficial financial effect for both aggregators and households. Furthermore, we identify the household features influencing possible price guarantees. The results here show the importance of the building type and its modernization status, highlighting the underestimated importance of thermal inertia.

Our study contributes to the broader discussion on demand response by providing a practical proposition to bridge the gap between household reluctance and the system-level benefits of dynamic pricing.

7.2. Real-world implementation

The primary prerequisite for implementing the proposed guarantee contracts is the deployment of smart meter infrastructure across participating households [28]. The availability of existing smart meter installations and the associated costs of new deployments represent important determinants of the viability of the presented guarantee schemes. Currently, smart meter penetration rates vary significantly across jurisdictions [97]. Economic considerations are particularly important: in Germany, for example, smart meter costs are regulated with annual fees capped at €50 and installation costs limited to €100 [13]. They are considerably cheaper in other European countries [7]. When households lack existing smart meter infrastructure and the associated deployment costs exceed potential energy savings, the economic rationale for participation is significantly undermined, potentially compromising the overall business case for price guarantee contract adoption.

Measurements and potential additional sensor data (e.g., indoor temperature measurements) must then be communicated in a secure and reliable way from the household to the aggregator [44]. Finally, control signals from the aggregator must be communicated to the households. There are several, already existing communication protocols, such as SG-Ready or Modbus for heat pumps, IEC 61,851 or ISO 15,118 for electric vehicles, [51] or SunSpec Modbus for BESS [48]. Further, there are communication standardization efforts for demand response, for instance, through EEBus [8]. In households, this demand response would then be managed through home energy management systems, which are already widely available (e.g., Kermani et al. [47]). Alternatives include the direct control of appliances [59]. Initial research has demonstrated control concepts for aggregating heat pump pools in day-ahead electricity markets through these standardized interfaces [30]. Another challenge is dealing with a lack of data. However, transfer learning techniques have shown potential for thermal modeling applications, enabling aggregators to develop accurate models for new households using minimal data through knowledge transfer from existing customer profiles [69,70]. Complementary approaches utilize reinforcement learning frameworks to address model uncertainties and real-time operational challenges. Ojand and Dagdougui [64] implemented a Q-learning-based model predictive control system for residential energy management, demonstrating how machine learning algorithms can adapt to operational uncertainties while maintaining system performance without requiring extensive historical datasets. The ultimate business model depends on a profit-sharing scheme between aggregators and households. There is a growing body of literature on fair pricing and profit sharing in electricity markets, for example, in energy sharing communities with PV and neighborhood battery storage [40]. Further, contractual questions also arise, such as the frequency of contract renewals, price guarantee renegotiation, and households that add new appliances. All these questions call for robust and reliable solutions and guidelines, which have to be established in future research and field trials. The resolution of these practical issues may further influence customers' willingness to subscribe to the concept, which should be analyzed in future studies. Further, the concept needs to align with regulatory approaches that limit discriminatory pricing. However, the design closely relates to the insurance business, which traditionally prices its services based on household characteristics [53].

7.3. Future work

Our study opens several avenues for future work, which are required to bring the concept into widespread use. The potential areas for future work can be distinguished by their focus, ranging from model improvements to real-time applications, household preferences, and portfolio optimization of aggregators.

For improving the underlying model, future research could enhance the granularity of the model by incorporating additional flexibility sources, such as electric vehicles, employing more advanced thermal models (e.g., 2R2C models), and accounting for variations in PV system configurations. In particular, considering electric vehicle charging flexibility, including bidirectional charging (i.e., vehicle-to-grid), would increase households' flexibility potential. This could lead to better guarantees for households. Furthermore, future research could also utilize higher computational resources to replace some of the simplified components (e.g., thermal modeling) with more detailed models, thereby achieving more sophisticated household flexibility modeling at the cost of increased complexity.

For real-time applications, it is essential to evaluate the demand response performance under operational foresight. To generate the underlying dataset with a Monte Carlo Simulation, the home energy management model of the analyzed households is optimized under perfect foresight, which we see as a fair assumption, given the theoretical character of our study. However, the practical implementation for aggregators would require an operation under the uncertainty of future setpoint profiles and household behavior. Previous literature has shown that this can be achieved well with Model Predictive Control algorithms, which can yield 63%–98% of profits realized under perfect foresight [43].

For the introduction of the suggested low-price guarantee concept, it is integral to understand consumer preferences towards it. A behavioral investigation into household perceptions and acceptance of such guarantees in future research would significantly enhance the understanding and practical applicability of this concept. A particularly important perspective for future research is the assessment of household risk-aversion factors and the associated willingness-to-adopt either dynamic tariffs or the suggested price guarantees. As we have discussed in this paper, households are largely risk-averse. Therefore, further including the utility of reduced price variance should tilt the balance further in favor of our proposed price guarantee approach. The corresponding utility could be formulated using a Cobb-Douglas utility function [83] balancing price level and variance. The exact parameterization of this function could be analyzed by conducting discrete choice experiments [27]. The estimated household utility from tariffs that balance price level and risk could then be used to refine our model and the decision support system for aggregators. Another valuable avenue for further research could be comparing dynamic pricing schemes where households actively manage their own demand with dynamic tariffs against automated home energy management system control from the aggregator. While such a study would have to rely on various, especially behavioral, assumptions, our framework could, in principle, be extended to include such considerations. This would provide insights into the trade-offs between user-managed flexibility and automated efficiency, highlighting under which conditions active household engagement or aggregator control may be preferable.

From an aggregator perspective, it is essential to investigate the selection and optimization of long-term electricity procurement strategies, such as futures contracts, in the context of a managed portfolio of households with price guarantees. Aggregators must balance the cost and availability of these contracts against the variability of household flexibility and market conditions. The methodology can be easily applied to other markets and regulatory scenarios. For instance, the feed-in tariffs considered in the home energy optimization problem can be replaced with a net metering scheme [72], and the distributions for the Monte Carlo simulation can be replaced with local values, weather, and price curves. Additionally, a comparative analysis of price guarantees across different international markets could provide valuable insights for future research.

Appendix A

COP parameters

In Table A.4, the temperature-dependent parameters for the polynomial fitting of the heat pump COP curve are depicted, based on [86].

Table A.4
Coefficients used in the COP calculation.

Coefficient	Value
c0	8.24
c1	0.158
c2	−0.195
c3	0.00101
c4	0.00148
c5	−0.00233
T_{ws}	50

PV and conditional BESS size distributions

In Fig. A.12, the empirically observed size of BESS is displayed, depending on the connected PV sizes.

Price components

In Table A.5, the fees and taxes that are added to the day-ahead spot market prices are depicted, based on Bundesnetzagentur [14] and der Energie-und Wasserwirtschaft [22]. The volume-weighted prices are calculated by weighting the day-ahead price curves with standard load profiles from Bundesverband der Energie- und Wasserwirtschaft e.V. [15], which also serve as input for the non-flexible household consumption E^{HH}.

Transformation of global horizontal irradiance

In Fig. A.13, an exemplary transformation of Global Horizontal Irradiance to Southern Vertical Irradiance is depicted.

Monte Carlo simulation convergence analysis based on central limit theorem

In Fig. A.14, the convergence of the Monte Carlo simulation is depicted according to the Central Limit Theorem, following the method of [92].

Quantile regression sensitivity analysis

In Figs. A.15 and A.16, the quantile regression results for the 0.1 and 0.9 quantiles are visualized, comparing guaranteed and realized prices for households across 2021, 2022, and 2023. Tables A.6 and A.7 present the mean and confidence interval widths for different quantiles, respectively, highlighting the impact of different quantile levels as a tool to balance competitiveness and the risk of guarantees. For instance, a 0.1 quantile leads to lower guarantees, which are often lower than the actual prices, leading to losses for the aggregator at the household level. Such a quantile level might be a reasonable choice for an aggregator that aims at winning new customers, whereas a 0.9 level leads to higher guarantees, which are less competitive, but also reduce the associated risk.

Table A.8 summarizes the comparison of electricity costs under aggregator-controlled and household-controlled flexibility scenarios.

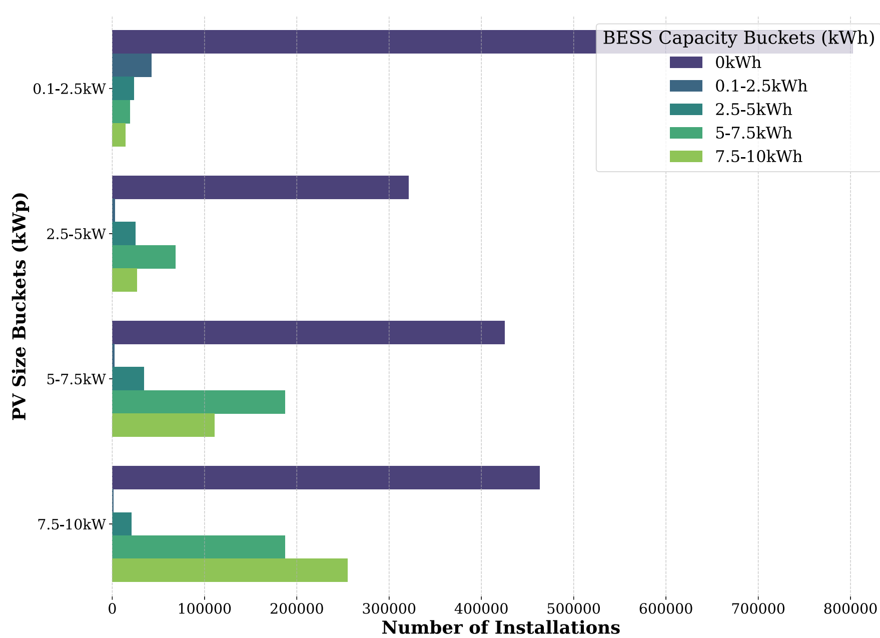


Fig. A.12. Distributions of PV size buckets and BESS capacity buckets.

Table A.5
Fees and taxes in €/kWh, based on der Energie-und Wasserwirtschaft [22].

Year	2018	2019	2020	2021	2022	2023
Mean yearly market price [€/kWh]	0.044469	0.037667	0.030471	0.096850	0.235446	0.095175
Grid Charges	0.072900	0.073900	0.077500	0.078000	0.080800	0.095200
EEG Umlage	0.067900	0.064100	0.067600	0.065000	0.018600	0.000000
Taxes	0.044100	0.044100	0.044100	0.044100	0.044100	0.044100
Volume Weighted Average Price [€/kWh]	0.231075	0.221882	0.221459	0.289756	0.379456	0.238699
Volume Weighted Average Price [€/kWh] with VAT	0.274979	0.264040	0.263536	0.344810	0.451553	0.284052

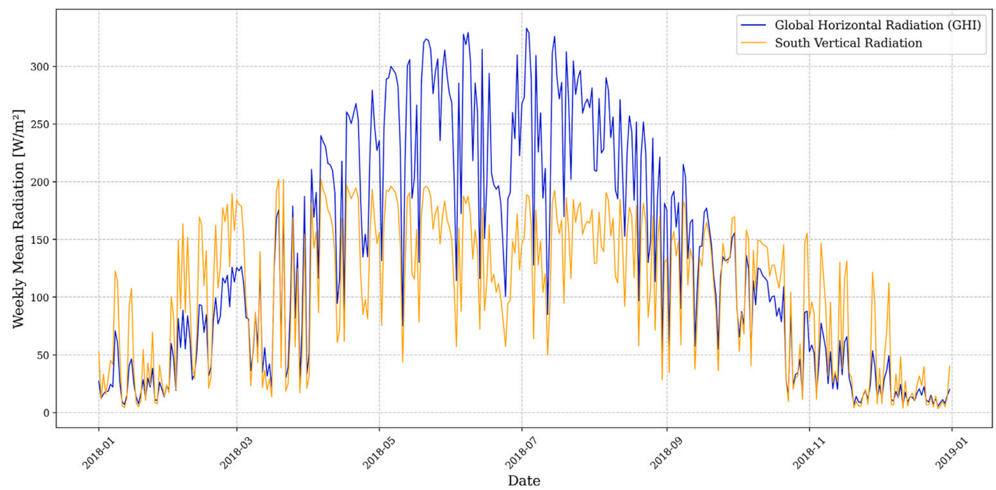


Fig. A.13. Transformation from Global Horizontal Irradiance to Southern Vertical Irradiance, exemplary illustrated based on Berlin weather data from 2018.

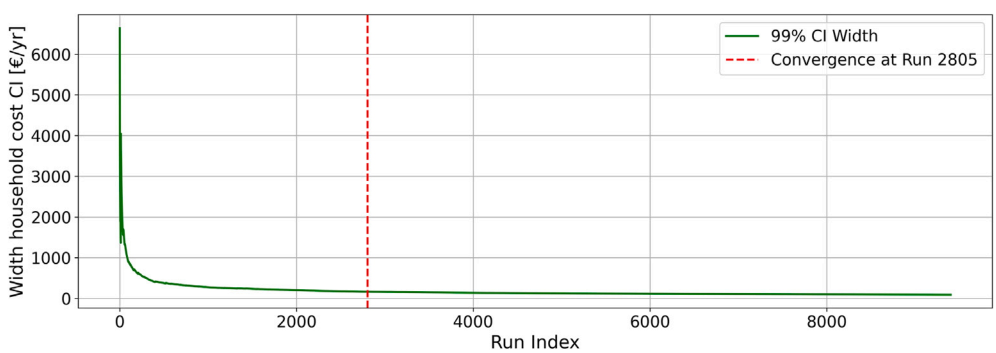
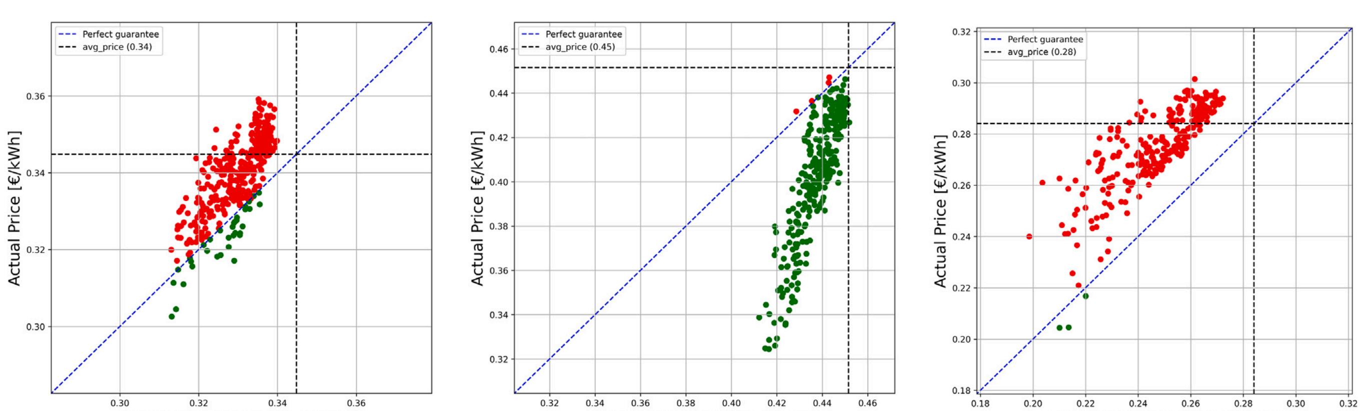
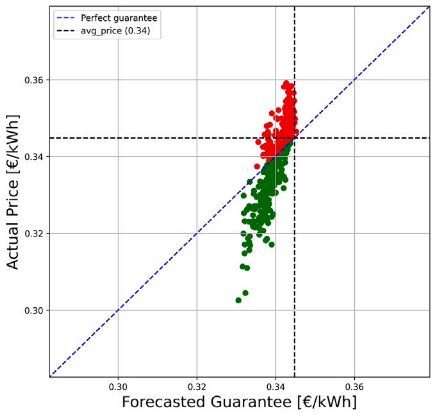


Fig. A.14. Confidence interval analysis based on the Central Limit Theorem, according to Yang [92].

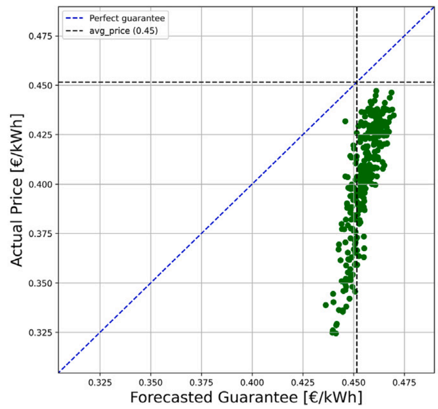


(a) 2021 (b) 2022 (c) 2023

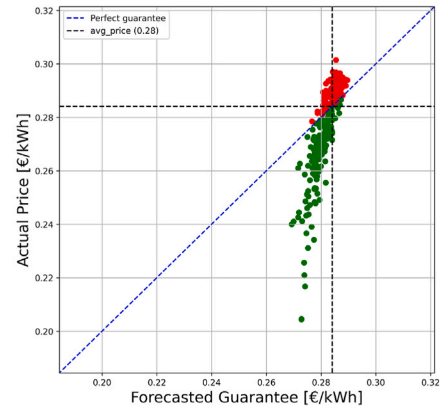
Fig. A.15. Quantile regression for 0.1 quantile: Comparison of guaranteed and realized prices per household. The blue line represents a perfect prediction (predicted costs = actual costs). The grey dotted lines represent the yearly average electricity price. Red dots represent a loss for the aggregator (guaranteed prices < actual prices), and green dots represent a profit (guaranteed prices > actual prices).



(a) 2021



(b) 2022



(c) 2023

Fig. A.16. Quantile regression for 0.9 quantile: Comparison of guaranteed and realized prices per household. The blue line represents a perfect prediction (predicted costs = actual costs). The grey dotted lines represent the yearly average electricity price. Red dots represent a loss for the aggregator (guaranteed prices < actual prices), and green dots represent a profit (guaranteed prices > actual prices).

Table A.6
(a) Mean over different quantiles.

Target year	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
2021	−4.288654	−65.755298	−27.226418	−15.846370	−4.288654	6.833473	21.598347	33.719610	61.848928
2022	459.028291	342.463387	378.127472	414.917185	459.028291	489.397181	509.442118	527.441974	567.534031
2023	3.061538	−150.497560	−65.444641	−26.195397	3.061538	31.770486	62.237874	93.061368	129.655953

Table A.7
(b) Interval Width over different quantiles.

Target year	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
2021	226.374622	268.246951	223.793984	235.008560	226.374622	200.421076	181.842471	182.793065	180.343278
2022	799.164416	691.732064	722.483228	775.815889	799.164416	815.233101	843.722611	873.416549	857.152743
2023	348.326632	496.142462	397.065325	349.168304	348.326632	318.929070	313.156979	257.537927	247.326130

Table A.8
Results per scenario and year.

Year	Aggregator controls flexibility	Household controls flexibility	Absolute change [€/kWh]	Percent change [%]
2021	0.339	0.358	0.019	5.652
2022	0.403	0.437	0.034	8.484
2023	0.274	0.295	0.021	7.705
All years	0.340	0.365	0.025	7.359

CRediT authorship contribution statement

Leo Semmelmann: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Steven O. Kimbrough:** Writing – review & editing, Methodology, Conceptualization. **Philipp Staudt:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Formal analysis, Conceptualization.

Declaration of generative AI in scientific writing

During the preparation of this work, the authors used Grammarly, ChatGPT 4o and Claude Sonnet 4 for language refinement and grammar correction. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

The source code of this study is available at https://github.com/leloq/Decision-Support-System-for-Electricity-Price-Guarantees.

References

[1] Ackermann S, Szabo A, Bamberger J, Steinke F. Design and optimization of performance guarantees for hybrid power plants. Energy 2022;239:121742.
[2] Aghaei J, Alizadeh M-I. Demand response in smart electricity grids equipped with renewable energy sources: a review. Renew Sustain Energy Rev 2013;18:64–72.
[3] Alabid J, Bennadji A, Seddiki M. A review on the energy retrofit policies and improvements of the UK existing buildings, challenges and benefits. Renew Sustain Energy Rev 2022;159:112161.

[4] Althaher S, Mancarella P, Mutale J. Automated demand response from home energy management system under dynamic pricing and power and comfort constraints. IEEE Trans Smart Grid 2015;6(4):1874–83.
[5] Angeli D, Dong Z, Strbac G. Exact aggregate models for optimal management of heterogeneous fleets of storage devices. IEEE Trans Control Netw Syst 2023.
[6] Aniello G, Bertsch V. Shaping the energy transition in the residential sector: regulatory incentives for aligning household and system perspectives. Appl Energy 2023;333:120582.
[7] Arthur D. Little. Digital energy: how smart meters will contribute to changing the energy landscape? Arthur D. Little Insights. Accessed Sep 22 2025.
[8] Ascher D, Albayrak S. A data-driven architecture for adaptive decentralized charging and energy management. In: 2024 IEEE PES innovative smart grid technologies Europe (ISGT EUROPE). IEEE; 2024. p. 1–5.
[9] Baeten B, Rogiers F, Helsen L. Reduction of heat pump induced peak electricity use and required generation capacity through thermal energy storage and demand response. Appl Energy 2017;195:184–95.
[10] Ballarini I, Corgnati SP, Corrado V. Use of reference buildings to assess the energy saving potentials of the residential building stock: the experience of tabula project. Energy Policy 2014;68:273–84.
[11] Berger M, Worlitschek J. A novel approach for estimating residential space heating demand. Energy 2018;159:294–301.
[12] Bruninx K, Pandžić H, Le Cadre H, Delarue E. On the interaction between aggregators, electricity markets and residential demand response providers. IEEE Trans Power Syst 2019;35(2):840–53.
[13] Bundesministerium für Wirtschaft und Klimaschutz. Bundesrat bestätigt Änderungen für schnelleren smart-meter-rollout. Retrieved from https://www.bundeswirtschaftsministerium.de/Redaktion/DE/Pressemitteilungen/2025/20250214-bundesrat-bestaetigt-aenderungen-fuer-schnelleren-smart-meter-rollout.html. Accessed Aug 14 2025.
[14] Bundesnetzagentur. Smard. https://www.smard.de/home. Accessed Dec 12 2024.
[15] Bundesverband der Energie- und Wasserwirtschaft e.V. Standardlastprofile strom. Retrieved from https://www.bdew.de/energie/standardlastprofile-strom/. Accessed Nov 7 2024.
[16] Burger S, Chaves-Ávila JP, Batlle C, Pérez-Arriaga IJ. A review of the value of aggregators in electricity systems. Renew Sustain Energy Rev 2017;77:395–405.
[17] Comfort BH. Stromverbrauch wärmepumpe - wissenswertes. Retrieved from, 2024. https://www.bosch-homecomfort.com/de/de/wohngebaeude/wissen/heizungsratgeber/waermepumpe/stromverbrauch-waermepumpe.
[18] Consiglio A, Cocco F, Zenios SA. Asset and liability modelling for participating policies with guarantees. Eur J Oper Res 2008;186(1):380–404.
[19] da Silva Pereira EJ, Pinho JT, Galhardo MAB, Macêdo WN. Methodology of risk analysis by monte carlo method applied to power generation with renewable energy. Renew Energy 2014;69:347–55.
[20] Luo, N. and Hong, T. Ecobee donate your data: 1, 000 homes in 2017. OSTI 2022.
[21] Schlemminger, M., Ohrdes, T., Schneider, E., Knoop, M. Dataset on electrical single-family house and heat pump load profiles in germany. Scientific data 2022;9(1):56.
[22] DER energie-und wasserwirtschaft (BDEW), b. Bdew strompreisanalyse. 2024. Retrieved from https://www.bdew.de/service/daten-und-grafiken/bdew-strompreisanalyse/.
[23] Destatis. Pressemitteilung nr. 038 vom 25. Juli 2024: neues zur statistik DER bevölkerung. Retrieved from https://www.destatis.de/DE/Presse/Pressemitteilungen/2024/07/PD24_N038_43.html. Accessed Dec 25 2024.
[24] Destatis. Raumwärme in privaten haushalten. Statistisches bundesamt. Retrieved from, 2024. https://www.destatis.de/DE/Themen/Gesellschaft-Umwelt/Umwelt/UGR/private-haushalte/Tabellen/raumwaerme-haushalte.html.
[25] Destatis. Stromverbrauch in privaten haushalten. Statistisches bundesamt. Retrieved from, 2024. https://www.destatis.de/DE/Themen/Gesellschaft-Umwelt/Umwelt/UGR/private-haushalte/Tabellen/stromverbrauch-haushalte.html.
[26] Emhofer J, Marx K, Sporr A, Barz T, Nitsch B, Wiesflecker M, Pink W. Experimental demonstration of an air-source heat pump application using an integrated phase change material storage as a desuperheater for domestic hot water generation. Appl Energy 2022;305:117890.
[27] Farsi M. Risk aversion and willingness to pay for energy efficient systems in rental apartments. Energy Policy 2010;38(6):3078–88.
[28] Faruqui A, Harris D, Hledik R. Unlocking the 53 billion savings from smart meters in the EU: how increasing the adoption of dynamic tariffs could make or break the eu's smart grid investment. Energy Policy 2010;38(10):6222–31.
[29] Finck C, Li R, Kramer R, Zeiler W. Quantifying demand flexibility of power-to-heat and thermal energy storage in the control of building heating systems. Appl Energy 2018;209:409–25.
[30] Fischer D, Triebel M-A, Selinger-Lutz O. A concept for controlling heat pump pools using the smart grid ready interface. In: 2018 IEEE PES innovative smart grid technologies conference Europe (ISGT-Europe). IEEE; 2018. p. 1–6.
[31] Fischer D, Wolf T, Wapler J, Hollinger R, Madani H. Model-based flexibility assessment of a residential heat pump pool. Energy 2017;118:853–64.
[32] Fitzpatrick P, D'Ettorre F, De Rosa M, Yadack M, Eicker U, Finn DP. Influence of electricity prices on energy flexibility of integrated hybrid heat pump and thermal storage systems in a residential building. Energy Build and E&B 2020;223:110142.
[33] Fraga C, Hollmuller P, Schneider S, Lachal B. Heat pump systems for multifamily buildings: potential and constraints of several heat sources for diverse building demands. Appl Energy 2018;225:1033–53.
[34] Freier J, von Loessl V. Dynamic electricity tariffs: designing reasonable pricing schemes for private households. Energy Econ 2022;112:106146.
[35] Guo B, Weeks M. Dynamic tariffs, demand response, and regulation in retail electricity markets. Energy Econ 2022;106:105774.
[36] Gurobi Optimization, LLC. Gurobi optimizer reference manual. 2025. Available at: https://www.gurobi.com.
[37] Hammersley J. Monte carlo methods. Springer Science & Business Media; 2013.
[38] Hartner M, Mayr D, Kollmann A, Haas R. Optimal sizing of residential pv-systems from a household and social cost perspective: a case study in Austria. Sol Energy 2017;141:49–58.
[39] Hedegaard RE, Pedersen TH, Petersen S. Multi-market demand response using economic model predictive control of space heating in residential buildings. Energy Build and E&B 2017;150:253–61.
[40] Henni S, Staudt P, Weinhardt C. A sharing economy for residential communities with pv-coupled battery storage: benefits, pricing and participant matching. Appl Energy 2021;301:117351.
[41] Holmgren WF, Hansen CW, Mikofski MA. Pvlib python: a Python package for modeling solar energy systems. J Open Source Softw 2018;3(29):884.
[42] Hubert T, Grijalva S. Modeling for residential electricity optimization in dynamic pricing environments. IEEE Trans Smart Grid 2012;3(4):2224–31.
[43] Junker RG, Kallesøe CS, Real JP, Howard B, Lopes RA, Madsen H. Stochastic nonlinear modelling and application of price-based energy flexibility. Appl Energy 2020;275:115096.
[44] Kabalci Y. A survey on smart metering and smart grid communication. Renew Sustain Energy Rev 2016;57:302–18.
[45] Katz J, Andersen FM, Morthorst PE. Load-shift incentives for household demand response: evaluation of hourly dynamic pricing and rebate schemes in a wind-based electricity system. Energy 2016;115:1602–16.
[46] Kelly JJ, Leahy PG. Optimal investment timing and sizing for battery energy storage systems. J Energy Storage 2020;28:101272.
[47] Kermani M, Adelmanesh B, Shirdare E, Sima CA, Carnì DL, Martirano L. Intelligent energy management based on scada system in a real microgrid for smart building applications. Renew Energy 2021;171:1115–27.
[48] Kini RL, Raker D, Katipamula S, Lutes R, Wu D, Kolln J. Interoperable energy storage control and communication framework development. In: 2025 IEEE electrical energy storage applications and technologies conference (EESAT). IEEE; 2025. p. 1–5.
[49] Kircher KJ, Zhang KM. Heat purchase agreements could lower barriers to heat pump adoption. Appl Energy 2021;286:116489.
[50] Kotthoff F, Muschner C, Tepe D, Pleßmann G, Hülk L. Open-mastr: a Python package to download and process the German energy registry marktstammdatenregister. J Open Source Softw 2024;9(100):6758.
[51] Krug F, Maier L, Müller D. Analyzing the performance of aggregators under communication protocol constraints. Sustain Energy Grids Netw 2025:101867.
[52] Le Dréau J, Heiselberg P. Energy flexibility of residential buildings using short term heat storage in the thermal mass. Energy 2016;111:991–1002.
[53] Li L-F, Wang J-F, Leung H. Using spatial analysis and Bayesian network to model the vulnerability and make insurance pricing of catastrophic risk. Int J Geogr Inf Sci 2010;24(12):1759–84.
[54] Li Y, Ou J, Gu C. Buyer guarantee and bailout in supplier finance with bankruptcy cost. Eur J Oper Res 2023;305(1):287–99.
[55] Li Z, Xie F, Zhang H, Zhang H. Signaling quality through price guarantee window for technology-related products. Eur J Oper Res 2024;313(2):669–77.
[56] Luo M, Wu S. A value-at-risk approach to optimisation of warranty policy. Eur J Oper Res 2018;267(2):513–22.
[57] Marktstammdatenregister. Mastr - marktstammdatenregister. Retrieved from https://www.marktstammdatenregister.de/MaStR. Accessed Dec 24 2024.
[58] McPherson M, Stoll B. Demand response for variable renewable energy integration: a proposed approach and its impacts. Energy 2020;197:117205.
[59] Meiers J, Ortleb M, Jonas D, Tadayon L, Frey G. Control strategies for heat pumps in a residential area under consideration of system operator benefits and grid stability. Energy Build and E&B 2025;332:115442.
[60] Meng Q, Xiong C, Mourshed M, Wu M, Ren X, Wang W, Li Y, Song H. Change-point multivariable quantile regression to explore effect of weather variables on building energy consumption and estimate base temperature range. Sustain Cities Soc 2020;53:101900.
[61] Moon JW, Han S-H. Thermostat strategies impact on energy consumption in residential buildings. Energy Build and E&B 2011;43(2–3):338–46.
[62] Nicolson M, Huebner G, Shipworth D. Are consumers willing to switch to smart time of use electricity tariffs? The importance of loss-aversion and electric vehicle ownership. Energy Res Soc Sci 2017;23:82–96.
[63] Nolting L, Praktiknjo A. Techno-economic analysis of flexible heat pump controls. Appl Energy 2019;238:1417–33.
[64] Ojand K, Dagdougui H. Q-learning-based model predictive control for energy management in residential aggregator. IEEE Trans Autom Sci Eng 2021;19(1):70–81.
[65] Pallante A, Adacher L, Botticelli M, Pizzuti S, Comodi G, Monteriu A. Decision support methodologies and day-ahead optimization for smart building energy management in a dynamic pricing scenario. Energy Build and E&B 2020;216:109963.
[66] Pallonetto F, Oxizidis S, Milano F, Finn D. The effect of time-of-use tariffs on the demand response flexibility of an all-electric smart-grid-ready dwelling. Energy Build and E&B 2016;128:56–67.
[67] Pena-Bello A, Burer M, Patel MK, Parra D. Optimizing PV and grid charging in combined applications to improve the profitability of residential batteries. J Energy Storage 2017;13:58–72.
[68] Pfenninger S, Staffell I. Long-term patterns of European PV output using 30 years of validated hourly reanalysis and satellite data. Energy 2016;114:1251–65.
[69] Pinto G, Messina R, Li H, Hong T, Piscitelli MS, Capozzoli A. Sharing is caring: an extensive analysis of parameter-based transfer learning for the prediction of building thermal dynamics. Energy Build and E&B 2022;276:112530.

[70] Raisch F, Krug T, Goebel C, Tischler B. Gentl: a general transfer learning model for building thermal dynamics. In: Proceedings of the 16th ACM international conference on future and sustainable energy systems; 2025. p. 322–33.
[71] Sachs O, Tiefenbeck V, Duvier C, Qin A, Cheney K, Akers C, Roth K. Field evaluation of programmable thermostats. Technical report, Fraunhofer Center for Sustainable Energy Systems (CSE), Cambridge, MA; 2012.
[72] Schelly C, Louie EP, Pearce JM. Examining interconnection and net metering policy for distributed generation in the united states. Renew Energy Focus 2017;22:10–19.
[73] Semmelmann L, Konermann M, Dietze D, Staudt P. Empirical field evaluation of self-consumption promoting regulation of household battery energy storage systems. Energy Policy 2024;194:114343.
[74] So KC, Song J-S. Price, delivery time guarantees and capacity selection. Eur J Oper Res 1998;111(1):28–49.
[75] Somers M, Whittaker J. Quantile regression for modelling distributions of profit and loss. Eur J Oper Res 2007;183(3):1477–87.
[76] Sperber E, Frey U, Bertsch V. Reduced-order models for assessing demand response with heat pumps–insights from the German energy system. Energy Build and E&B 2020;223:110144.
[77] Staudt P, Dann D. Perceived complexity and effectiveness of dynamic electricity rate designs for smart markets. Appl Energy 2025;394:126042.
[78] Stute J, Klobasa M. How do dynamic electricity tariffs and different grid charge designs interact?-implications for residential consumers and grid reinforcement requirements. Energy Policy 2024;189:114062.
[79] Stute J, Kühnbach M. Dynamic pricing and the flexible consumer–investigating grid and financial implications: a case study for Germany. Energy Strategy Rev 2023;45:100987.
[80] Urban, Timothy L. Establishing delivery guarantee policies. Eur J Oper Res 2009;196(3):959–67.
[81] Vaillant Group. Pufferspeicher allstor exclusiv. Retrieved from https://www.vaillant.at/privatanwender/produkte/pufferspeicher-allstor-exclusiv-9792.html. Accessed Dec 12 2024.
[82] Van Lint JWC, van Zuylen HJ. Monitoring and predicting freeway travel time reliability: using width and skew of day-to-day travel time distribution. Transportation Research Record 2005;1917(1):54–62.
[83] Varian HR, Varian HR. Microeconomic analysis, vol. 3. Norton New York; 1992.
[84] Vehviläinen I, Keppo J. Managing electricity market price risk. Eur J Oper Res 2003;145(1):136–47.
[85] Verbraucherzentrale Bundesverband e.V. Dynamische stromtarife 2024: repräsentative befragung im auftrag DER marktbeobachtung energie. Retrieved from https://www.vzbv.de/. 2024. Survey conducted by forsa, July 11–25, 2024, based on 1, 001 households in Germany.
[86] Verhelst C, Logist F, Van Impe J, Helsen L. Study of the optimal control problem formulation for modulating air-to-water heat pumps connected to a residential floor heating system. Energy Build 2012;45:43–53.
[87] Visual Crossing. Visual crossing weather. Retrieved from, 2024. https://www.visualcrossing.com/.
[88] Wang C, Chen X, Jin W, Fan X. Credit guarantee types for financing retailers through online peer-to-peer lending: equilibrium and coordinating strategy. Eur J Oper Res 2022;297(1):380–92.
[89] Wang D, Zheng W, Wang Z, Wang Y, Pang X, Wang W. Comparison of reinforcement learning and model predictive control for building energy system optimization. Appl Therm Eng 2023;228:120430.
[90] Wang Z, Chen Y, Li Y. Development of RC model for thermal dynamic analysis of buildings through model structure simplification. Energy Build and E&B 2019;195:51–67.
[91] Winzer C, Ramírez-Molina H, Hirth L, Schlecht I. Profile contracts for electricity retail customers. Energy Policy 2024;195:114358.
[92] Yang J. Convergence and uncertainty analyses in monte-carlo based sensitivity analysis. Environ Model Software 2011;26(4):444–57.
[93] Yang Y, Javanroodi K, Nik VM. Climate change and energy performance of European residential building stocks–a comprehensive impact assessment using climate big data from the coordinated regional climate downscaling experiment. Appl Energy 2021;298:117246.
[94] Zhang L, Good N, Mancarella P. Building-to-grid flexibility: modelling and assessment metrics for residential demand response from heat pump aggregations. Appl Energy 2019;233:709–23.
[95] Zhang Y, Tian X, Zhao Y, Zhang C, Zhao Y, Lu J. A prior-knowledge-based time series model for heat demand prediction of district heating systems. Appl Therm Eng 2024:123696.
[96] Zhou K, Cheng L, Lu X, Wen L. Scheduling model of electric vehicles charging considering inconvenience and dynamic electricity prices. Appl Energy 2020;276:115455.
[97] Zhou S, Brown MA. Smart meter deployment in Europe: a comparative case study on the impacts of national policy schemes. J Clean Prod 2017;144:22–32.