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System-wide benefits of temporal alignment of wholesale–retail electricity prices

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ABSTRACT

Exposing residential consumers to real-time pricing (RTP) can yield significant efficiency gains, but may also pose challenges due to the inherent complexity. Using an extensive spectrum of temporal granularities for retail electricity pricing, we analyze to what extent these capture the benefits of RTP while concurrently considering the influence of three distribution tariff types in distorting the pricing signal. Via a mixed complementarity model, we consider both operational and investment decisions at retail as well as wholesale levels, accounting for their interdependencies. Our analysis reveals three key findings. Firstly, we find that decreasing temporal granularity of retail electricity prices increases total system cost due to an increasingly inefficient generation mix, however, three-hourly or six-hourly pricing can approximate RTP benefits. Secondly, decreasing temporal granularity of retail electricity prices raises average offtake and lowers average injection prices for consumers due to changes in wholesale market prices as well as consumption patterns of consumers. Thirdly, capacity-based tariffs reduce system offtake peaks and associated price increases by incentivizing battery discharge during peak consumption while volumetric tariffs, over-incentivizing solar PV investments, result in highest offtake prices and injection peaks.

1. Introduction

With growing adoption of distributed energy resources (DER), such as solar photovoltaics (PV) and battery energy storage systems (BESS), distribution systems transition from passive to active networks encompassing consumers with diverse load and generation profiles. This highlights the importance of sending price signals, including distribution tariffs and retail electricity prices,[2] that reflect drivers of system costs and are consistent with one another [2].

Historically, residential consumers have been exposed to constant electricity prices. Lack of exposure to wholesale prices for electricity precludes consumer operational and investment decisions from being system optimal, introducing additional costs and economic inefficiencies [3,4]. Allowing retail electricity prices to be more cost-reflective by means of temporal variation is generally viewed to have a number of benefits, among which: reducing the dead-weight loss arising from differences in wholesale and retail electricity prices [5,6] better aligning the distributed decisions with the efficient operation and planning of the power system [7], reducing the need for back-up generation capacity [8] and yielding greater distributional equity [9]. Furthermore, the transition to higher demand elasticity rates, suggests a future landscape where economic inefficiencies due to 'mispricing' may become even more pronounced, emphasizing the urgency for policies that ensure pricing mechanisms accurately reflect the underlying costs of electricity provision [6].

Several time-varying retail electricity pricing schemes of diverse complexity exist. These differ in (1) temporal granularity, meaning the frequency with which retail electricity prices change and (2) timeliness, meaning the delay between when the retail electricity price is set vs. in effect, or in other words, how dynamic the retail price is with regards to real-time market conditions [10].[3] Currently, in the European Union (EU), time-of-use (TOU) pricing is the most common, being applied in at least 17 member states [11]. In TOU pricing, prices vary in blocks

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[2] Throughout the text we will use the terms 'distribution tariff' to refer to network charges, and 'retail electricity prices' to refer to the electricity prices, seen by residential consumers.

[3] For a complete review on time-varying electricity pricing schemes we refer interested readers to [1].

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Nomenclature

Parameters

δ	Self-discharge rate of storage.
$\overline{w^{Inj}}$	Maximum injection power, MW.
$\overline{w^{off}}$	Maximum offtake power, MW.
Π_d	Weight of representative day d.
$AF^{gen}_{d,t,k}$	Availability factor of generator k on day d, hour t.
$AF^{pv}_{d,t,j}$	Availability factor of solar PV of consumer j on day d, hour t.
CR	Charge/discharge rate of storage.
$D_{d,t,j}$	Demand of consumer j on day d, hour t, MWh.
$D^{nres}_{d,t}$	Non-residential demand on day d, hour t, MWh.
IC^{gen}_k	Annualized investment cost of generator k, €/MW/year.
T_{CAP}	Capacity distribution tariff, €/MW.
T_{FIX}	Fixed distribution tariff, €/year.
T_{VOL}	Volumetric distribution tariff, €/MWh.
VC_k	Variable cost of generator k, €/MWh.
η^{rs}_{ch}	Charging efficiency of residential storage.
η^{gs}_{ch}	Charging efficiency of grid-scale storage.
η^{rs}_{dc}	Discharging efficiency of residential storage.
η^{gs}_{dc}	Discharging efficiency of grid-scale storage.
η^{rsi}	Efficiency of residential storage inverter.
η^{gsi}	Efficiency of grid-scale storage inverter.
PIC^{rs}_j	Perceived, annualized investment cost of storage for consumer j, €/MWh/year.
PIC^{rsi}_j	Perceived, annualized investment cost of storage inverter for consumer j, €/MW/year.
IC^{gs}	Annualized investment cost of grid-scale storage, €/MWh/year.
IC^{gsi}	Annualized investment cost of grid-scale storage inverter, €/MW/year.
PIC^{pv}_j	Perceived, annualized investment cost of solar PV panel for consumer j, €/MW/year.
PIC^{pvi}_j	Perceived, annualized investment cost of solar PV inverter for consumer j, €/MW/year.
$\overline{cap^{pv}}$	Maximum capacity of solar PV, MW.
$\overline{cap^{s}}$	Maximum capacity of residential storage, MWh.

Sets

$\mathcal{D}$	Set of representative days.
$\mathcal{J}$	Set of representative consumers.
$\mathcal{K}$	Set of transmission level generators.
$\mathcal{M}$	Set of months.
$\mathcal{T}$	Set of hours.

Variables

$\lambda^{inj}_{d,t}$	Retail electricity injection price on day d, hour t, €/MWh.
$\lambda^{off}_{d,t}$	Retail electricity offtake price on day d, hour t, €/MWh.
$\lambda_{d,t}$	Wholesale electricity price of day d, hour t, €/MWh.
cap^{gen}_k	Capacity of generator k, MW.
$g^{gen}_{d,t,k}$	Generation of generator k on day d, hour t, MWh.
$peak_{m,j}$	Peak offtake of consumer j in month m, MW.
$w^{inj}_{d,t,j}$	Electricity injection of consumer j on day d, hour t, MWh.
$w^{off}_{d,t,j}$	Electricity offtake of consumer j on day d, hour t, MWh.
cap^{rs}_j	Capacity of storage of consumer j, MWh.
cap^{rsi}_j	Capacity of storage inverter of consumer j, MW.
cap^{gs}	Capacity of grid-scale storage, MWh.
cap^{gsi}	Capacity of grid-scale storage inverter, MW.
cap^{pv}_j	Capacity of solar PV panel of consumer j, MW.
cap^{pvi}_j	Capacity of solar PV inverter of consumer j, MW.
$ch^{rs}_{d,t,j}$	Energy charged to consumer j storage on day d, hour t, MWh.
$ch^{gs}_{d,t}$	Energy charged to grid-scale storage on day d, hour t, MWh.
$dc^{rs}_{d,t,j}$	Energy discharged from consumer j storage on day d, hour t, MWh.
$dc^{gs}_{d,t}$	Energy discharged from grid-scale storage on day d, hour t, MWh.
$e^{rs}_{d,t,j}$	Energy content of consumer j storage on day d, hour t, MWh.
$e^{gs}_{d,t}$	Energy content of grid-scale storage on day d, hour t, MWh.
$g^{pv}_{d,t,j}$	Solar PV generation of consumer j on day d, hour t, MWh.
$Inj_{d,t}$	Total injection of all consumers on day d, hour t, MWh.
$Off_{d,t}$	Total offtake of all consumers on day d, hour t, MWh.

of time in a preset way (e.g. peak/off-peak). Additionally, prices may be determined months in advance, thus may not be wholly reflective of market conditions. At the other end of the spectrum is real-time-pricing (RTP), wherein prices are set day-ahead or in real-time, following the same temporal granularity as wholesale electricity prices.

Different pricing mechanisms entail distinct implications for competing factors of interest, including price volatility, operational reliability, and economic efficiency [12]. While RTP, in terms of economic efficiency, outperforms second-best pricing schemes, such as TOU, its inherent complexity may, in practice, pose challenges. Increasing price volatility can, for example, reduce the market's robustness by making it more vulnerable to fluctuations or unpredictability in electricity demand and generation, compromise system stability [12] and pose difficulty for consumers to adapt their consumption patterns, exposing them to greater financial risk [13]. RTP can trigger further controversy as it may be viewed as an attempt to commercialize what is traditionally seen as a public good, immune to market forces [9]. In light of these considerations, it is relevant to evaluate the extent to which alternative pricing resolutions, less susceptible to the aforementioned practical disadvantages, can approximate the market outcomes achieved by RTP.

On top of the electricity component, residential electricity bills also comprise regulated components such as distribution costs, taxes and levies which can distort electricity price signals. Among these components, distribution tariffs, used to recover the costs of distribution system operators (DSO), may dominate, forming a significant distortion [14]. Distribution tariffs determine how network costs are allocated to end-consumers. Commonly used distribution tariffs include and combine volumetric energy charges (€/kWh), fixed charges per connection point (€/year) and capacity-based charges (€/kW) [4].

In an era of increasing DER uptake, distribution tariffs need to anticipate new sets of actions available to consumers. Historically used policies of volumetric distribution tariffs combined with net metering[4]

[4] In net-metering consumers are billed solely for their annual net electricity consumption from the grid when charged distribution tariffs.

now present inefficiencies including too few price signals to incentivize optimal network utilization and the occurrence of cross-subsidies [2]. Non-solar households, potentially unable to afford solar panels, end up subsidizing the portion of network costs not covered by solar PV owners, a ‘reverse Robin Hood’ effect [15]. As such, there is growing consensus among regulators and academics in favor of replacing volumetric distribution tariffs for capacity-based tariffs [7,16,17].

In this paper, tailored to EU market design, we seek to answer the following research question: how does the temporal granularity of retail electricity prices interact with different distribution tariffs, considering the interplay between consumers' decisions and the rest of the electric power system? We analyze eight different temporal resolutions for retail electricity pricing, each in combination with a volumetric (VOL), capacity-based (CAP) or fixed (FIX) distribution tariff, yielding 24 cases in total.

As we will discuss in more detail in Section 2, we contribute to the literature in several key aspects. Firstly, we evaluate temporal granularities of retail electricity prices that were largely overlooked in existing literature. While recognizing the potential of RTP to achieve optimal economic efficiency, our research endeavors to explore alternatives aiming to comprehend the extent of benefits achievable with pricing schemes of lower temporal granularity that may mitigate some of the disadvantages inherent to RTP. We broaden the conversation beyond commonly studied lower granularity pricing schemes, such as TOU, providing a spectrum of viable options for enhancing the efficiency of electricity markets. Secondly, for all temporal granularities of retail electricity prices we consider the interaction with distribution tariffs, giving insight as to how these may distort the electricity price signal and the extent to which these distortions impede market efficiency. Finally, unlike the prevailing operational focus found in current literature, our modeling approach diverges by embracing a holistic perspective, wherein we envision a fully integrated system. In this paradigm, retail electricity prices, responsive to consumer decisions, reflect market conditions, while operational and investment choices at both retail and wholesale levels influence one another, underscoring the recognition that the power system adapts to the actions of consumers. This multifaceted approach enhances our understanding of electricity pricing mechanisms, offering insights that can inform more nuanced and effective market mechanisms.

Throughout this paper, a main performance metric is the total system cost, presented in Appendix B. In our context, maximizing welfare and minimizing total system cost are equivalent because demand for electricity is inelastic. Efficiency losses are then computed as deviations from the optimal system cost, typically found under RTP.

The remainder of this paper is structured as follows. The next section situates our work within the related literature. In Section 3, the reader can find the tariffs evaluated by the study and model description. Section 4 outlines the data and assumptions used in the case study. Results and discussion of the case study can be found in Section 5. Section 6 concludes.

2. Literature

Our study connects two interrelated bodies, contributing to the broader context of market design for distribution grids. It is part of the discussion on the benefits of increased temporal granularity of retail electricity prices, which we detail in Section 2.1, as well as the debate, Section 2.2, on how distribution tariff design affects consumer decisions. In combining these two bodies of literature we illustrate the interplay between different distribution tariffs and time-varying retail pricing as done in few other studies outlined in Section 2.3.

2.1. *Time-varying retail electricity pricing*

Several authors have explored common alternatives to RTP, seeking to understand the magnitude of benefits attainable through pricing strategies with lower temporal granularity. In studies including [18–20], simulation models are commonly used to understand how much of the welfare benefits of RTP can be captured by TOU pricing. Borenstein [18] studies the long-run effects of residential RTP and TOU pricing, finding that the latter captures only 20% of the efficiency gains. Studying the short-run welfare effects of TOU vs. RTP, Holland and Mansur [19] and Spees and Lave [20], also conclude that TOU pricing is a poor substitute for RTP. These studies model predominantly thermal systems with little wind or solar generation. Schittekatte et al. [21] using more recent US-based system operator data including greater solar and wind generation, focus on a context with high volumes of intraday shiftable loads such as electric vehicles and heat pumps. They compute the correlations between wholesale prices and TOU prices, confirming via simulations that TOU electricity prices can replicate up to 70% of the load shifting potential provided under RTP. The common caveat in the literature studying time-varying retail pricing is the use of stylized models that assume prices, demand, and generation capacities. The wholesale level is taken as fixed, disregarding developments based on the retail level's response to electricity prices.

2.2. *Distribution tariffs*

The academic literature on distribution tariffs has focused on tariff design for seeking greater cost causality and avoiding the ‘reverse Robin Hood’ effect occurring under commonly used volumetric charging. In [22], results confirm that volumetric distribution tariffs over-incentivize the adoption of solar PV, however, depending on DER costs, capacity-based charges may too severely distort investment decisions of prosumers. Eid et al. [23] find that capacity-based charges incentivize local storage and self-consumption. The authors add that fixed charges are not recommended due to absence of cost reflectivity and storage incentives. Simshauser [24] warn that if capacity-based charges overstate the value of peak load these may over-incentivize BESS investments. Taking a closer look at the impacts on load, Passey et al. [25] find that capacity tariffs, albeit reducing individual peaks, may not be effective in reducing network peak. Using real-world data Ansarin et al. [26] also find that a peak-coincident capacity charges do not provide efficient signals for reducing grid peak but do mitigate the ‘reverse Robin Hood’ effect. By means of econometric analysis, Borenstein [27] argues that there is no ideal policy but a combination of higher fixed charges and an adder to time-varying volumetric charges would be the least bad option in steering consumer decisions and recovering sunk network costs. With the exception of [22] in which consumers are exposed the wholesale price of electricity, the mentioned studies assume flat retail electricity prices. None pause to reflect on how distribution tariffs in combination with retail electricity price design choices may affect consumers. The wholesale level is considered fixed in these studies.

2.3. *Time-varying retail electricity pricing & distribution tariffs*

Few studies combine distribution tariffs and time-varying retail electricity pricing. Studies [14,28,29] investigate how different tariff designs affect consumer decisions under RTP. Steen et al. [28] conclude that, compared to a volumetric tariff, customers make greater savings under capacity-based tariff and a reduction in peak demand occurs. In [29], focus lies on how system-friendly the operation of consumer PV-battery systems may be. Findings illustrate that when RTP is combined with higher fixed charges, as opposed to volumetric charges, so-called ‘market-alignment’ of PV-battery systems is improved as the overall wholesale electricity price signal shape and incentives are not offset. While these studies disregard network cost recovery, [14] does not and finds, considering sunk network costs, that all tariff structures, bar the fixed tariff, incentivize prosumers to deviate from 'energy-optimal' actions, i.e. ones minimizing total system energy costs, to reduce their distribution costs.

The literature rarely explores *varying* temporal granularities for electricity pricing in combination with distribution tariffs. In [30], the authors evaluate the effects of constant, TOU, critical peak and RTP in combination with distribution tariffs on energy bills and load profiles of consumers within the context micro-grids. Results indicate that under capacity-based distribution tariffs, time-varying electricity retail pricing has little impact on energy bills as well as load and generation peaks. In [31,32], consumer bill savings from solar PV are estimated under flat, TOU and real-time pricing schemes combined with fully volumetric distribution tariffs or ones including fixed charges. Findings illustrate that greater temporal granularity of electricity prices increases bill savings but moving from a fully volumetric distribution tariff to one including a fixed charge, under net metering, erodes those savings. Beyond the fact that these studies look at a narrow range of temporal granularities for electricity pricing all also use operational models with focus on retail level. No investment decisions are taken into account and the use of exogenous wholesale prices means that the feed-backs between prosumers' decisions and market prices are disregarded.

2.4. Research gap & contribution

This review of the literature indicates that there exist a plethora of studies separately considering the effects of time-varying retail electricity pricing and distribution tariffs, with few considering the whole-system effects. The few that do, tend to focus on common pricing schemes without addressing a more complete spectrum of temporal granularities for electricity pricing. This gap is significant because by focusing solely on known or common time-varying electricity pricing schemes, we overlook the potential for implementing intermediate temporal granularities. Alternatives that may mitigate some of the practical disadvantages of RTP, such as system unpredictability and the challenge of consumer adaptability to hourly price changes, while still capturing a higher percentage of RTP's economic benefits compared to pricing schemes like TOU. Furthermore, none of the mentioned studies evaluate how time-varying retail electricity prices combined with distribution tariffs shape investments in residential solar PV and BESS assets and how these, in turn, impact wholesale prices and generation capacity investments. We thus contribute to the literature by providing such a study, which considers a wide range of temporal granularities for retail electricity pricing, in combination with distribution tariffs, accounting for the feedback in investments, operations and prices between wholesale and retail levels. Our aim is to provide a stylistic study which unveils the general mechanisms that can occur in an electric power system rather than predicting specific real-world outcomes.

3. Methods

The general model structure is introduced in Section 3.1, the utilized temporal granularities for retail electricity pricing and distribution tariffs are shown in Section 3.2 while Section 3.3 illustrates how retail prices are calculated. The mathematical formulations of each agent's optimization problem is presented in Section 3.4, and an algorithmic procedure for computing the solution is detailed in Section 3.5.

3.1. Model structure

We develop a model describing a non-cooperative Nash Game between different agents within wholesale as well as retail level. The model is inspired by traditional electricity market equilibrium models which simulate a long-run equilibrium in the wholesale electricity market [33]. Each agent simultaneously optimizes individual investment and operational decisions for a whole year based on annualized investment cost values.[5] The entire year is modeled, with hourly resolution, by means of a set of representative days with associated weights. Agents are coupled through market clearing constraints to ensure a balance between electricity supply and demand. Overall, the model output can be interpreted as a Nash equilibrium where no agent in the model can improve its outcome by adapting its own strategy given the decisions of other agents.

Fig. 1 provides a schematic overview of the model, in which we make the following assumptions. All agents are rational price-takers in a deterministic setting, implying perfect foresight. The power system modeled in the game is an isolated system with no spatial granularity and is assumed to be a greenfield model. Agents are limited to technology-aggregated conventional generators, one renewable (wind) generator,[6] a grid-scale battery operator and a set of representative residential consumers having inelastic demand but the ability to invest in BESS as well as solar PV systems. Inelastic, non-residential load is also included in the model as a parameter.

Residential consumers consider only energy, distribution, and investment costs, ignoring other expenses such as retail margins and taxes. Retail electricity prices are perfectly predictable, with consumers reacting optimally to price signals, potentially possible through automation. Consumers' demand flexibility is approximated via the inclusion of storage as an investment option. Through storage, consumers have the capability to adjust their consumption patterns making price-based decisions related to the timing of energy use.[7] Finally, all residential consumers are charged the same retail prices and are all subject to the same type of network tariff.

3.2. Prices and tariffs under consideration

We examine eight options of temporal granularity for retail electricity prices, as illustrated in Fig. 2, and combine each granularity with one of three distribution tariff types.

We consider RTP (H1) as well as seven other options, that reflect the average wholesale price over: 3 h (3H), 6 h (6H), 12 h (12H), one day (24H), one month (1M), one quarter (3M) and one year (12M). In our RTP option, namely H1, wholesale, and retail electricity prices, for both offtake, and injection, are one and the same. Prices differ from hour to hour and day to day. In the other options, retail prices for injection and offtake are the average of wholesale prices over the designated hours in the averaging window, weighted with total consumer injection and offtake (see Fig. 2), as is common practice. Consumers are billed for consumption and remunerated for injection according to offtake price and injection price.

For network tariffs we consider, separately, the three most common ones. The first option is the volumetric tariff (VOL), billing consumers for each kWh of electricity they offtake. The second option is the capacity tariff (CAP), billing consumers based on their individual monthly peak offtake, inspired by the Flemish capacity-tariff [34]. The third option is the fixed tariff (FIX), whereby every residential consumer pays the same lump sum per year independent of their injection or offtake pattern.

[5] Agents thus implicitly assume that all forthcoming years within the investment's lifespan will resemble the year used for modeling.

[6] The renewable generator will be operated following market signals. As such, we ignore implications from distorting measures such as subsidy mechanisms or priority dispatch.

[7] We opt not to model demand flexibility through demand shifting since consumers can invest in batteries for similar effects. While demand response measures may reduce battery investments, the underlying consumption patterns and subsequent conclusions drawn from our study remain unaffected by this decision.

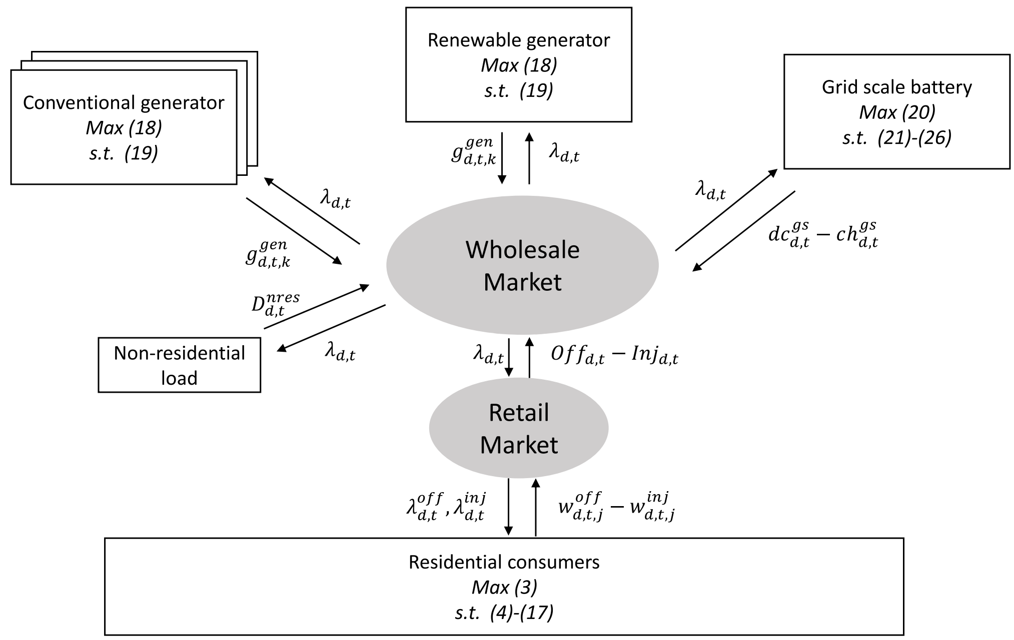

Fig. 1. Schematic overview of the non-cooperative game. Residential consumers will get retail offtake/injection prices while other agents receive wholesale market prices. The offtake/injection prices remain constant per averaging period.

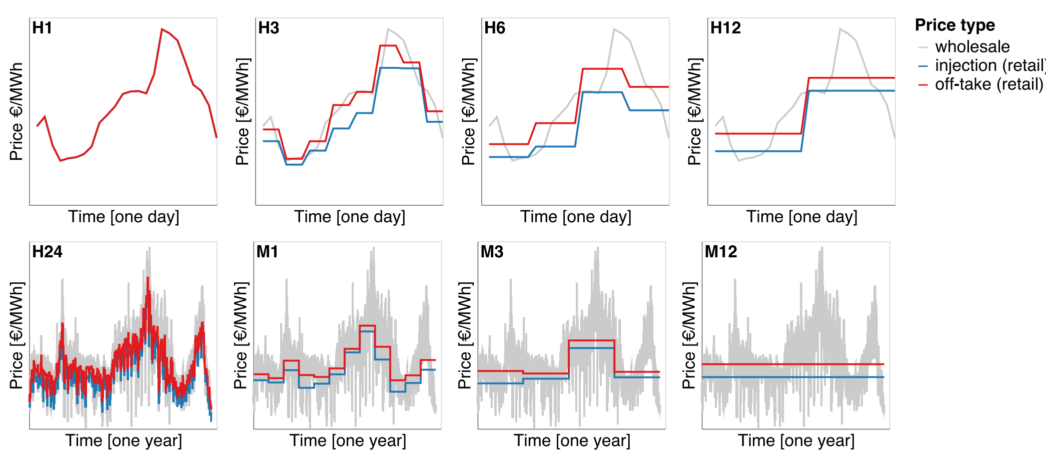

Fig. 2. Illustration of the temporal granularities for retail electricity prices considered in the study, from hourly (H1) pricing to yearly (M12). To better illustrate the price granularity in question, the x-axis either represents a day (H1–H12, top row) or one full year (H24 to M12, bottom row). Note that in H1 cases, wholesale, injection and offtake prices overlap.

3.3. Retail price calculation

The retail price signal received by households can be seen as the weighted average wholesale price. This pricing scheme is commonly used in various regions, such as Flanders in Belgium, where the retail offtake and injection electricity price for households are determined based on the Real Load Profiles (RLPs) or Synthetic Production Profiles (SPPs) of all households in one DSO zone [35]. For one specific averaging period b, the offtake and injection price can be calculated by averaging the hourly wholesale market price λ_t, weighted by the total hourly offtake (Off_t) and injection (Inj_t) from all residential prosumers in this period. Injection prices are typically lower than offtake prices. This is because wholesale prices during instances of injection are lower compared to offtake instances. In cases where the total injection or offtake during one averaging period is zero, a simple average will be taken. Different granularity cases result in varying lengths of the averaging period b, which in turn leads to different retail prices. The offtake and injection price during a specific pricing period (b) can be calculated by Eqs. (1) and (2) respectively,[8] in which Π_d is the representative weight of day d.

$$\lambda_b^{off} = \frac{\sum_{t\in b} \Pi_d \cdot \lambda_t \cdot Off_t}{\sum_{t\in b} \Pi_d \cdot Off_t} \tag{1}$$

$$\lambda_b^{inj} = \frac{\sum_{t\in b} \Pi_d \cdot \lambda_t \cdot Inj_t}{\sum_{t\in b} \Pi_d \cdot Inj_t} \tag{2}$$

The injection price is always set to be less than or equal to the offtake price in the corresponding period to ensure that consumers cannot exploit the price difference by purchasing energy at a lower price and selling it back to the grid at a higher price. It is important to note that all prices are endogenous to the mixed complementarity problem, but treated as parameters in agents' independent decision problems, which we describe in the following section.

[8] These conditions would correspond to the KKT-conditions of a supplier in a perfectly competitive retail market if explicitly modeled.

3.4. Mathematical formulation

In this section, the optimization problems of all individual agents are discussed in detail. While all agents see an annualized investment cost (IC), heterogeneity in consumer decision-making processes leads us to introduce the term perceived annualized investment cost (PIC). This variation is attributed to diverse risk preferences, perceptions of market conditions, future uncertainties, and other factors that influence individual discount rates and, consequently, the perceived cost of DER investments.

3.4.1. Residential consumers

The objective of each residential consumer is to minimize their yearly electricity bill (3). This bill has energy, investment and distribution components. The energy component is governed by offtake ($\lambda^{off}_{d,t}$) and injection prices ($\lambda^{inj}_{d,t}$). A consumer decides how much to offtake and inject according to variables $w^{off}_{d,t,j}$ and $w^{inj}_{d,t,j}$. In terms of investment components, the consumer decides the capacity they wish to invest in for solar PV (cap^{pv}_j), BESS (cap^{rs}_j) and respective inverters ($cap^{pvi}_j$and cap^{rsi}_j) according to their perceived investment costs for each technology: PIC^{pv}_j, PIC^{pvi}_j, $PIC^{rs}_j$and PIC^{rsi}_j. Within the distribution component, T_{FIX}, T_{VOL} and T_{CAP} are parameters governing the distribution tariff value.[9] Further operational decision variables of the consumer are, on an hourly basis: how much they generate from solar PV ($g^{pv}_{d,t,j}$) and how much energy they charge/discharge to/from their battery ($ch^{rs}_{d,t,j}$, $dc^{rs}_{d,t,j}$), which in turn, defines the energy content of their battery ($e^{rs}_{d,t,j}$). A consumer solves the following optimization problem:

$$\min_{x_{j\in\mathcal{J}}} : \sum_{d\in\mathcal{D},t\in\mathcal{T}} \Pi_d \cdot (\lambda^{off}_{d,t} \cdot w^{off}_{d,t,j} - \lambda^{inj}_{d,t} \cdot w^{inj}_{d,t,j}) + PIC^{pv}_j \cdot cap^{pv}_j$$
$$+ PIC^{pvi}_j \cdot cap^{pvi}_j + PIC^{rs}_j \cdot cap^{rs}_j + PIC^{rsi}_j \cdot cap^{rsi}_j$$
$$+ (T_{FIX} + T_{VOL} \cdot \sum_{d\in\mathcal{D},t\in\mathcal{T}} w^{off}_{d,t,j} \cdot \Pi_d + T_{CAP} \cdot \sum_{m\in\mathcal{M}} peak_{m,j})$$
$$x_j \in \{w^{off}_{d,t,j}, w^{inj}_{d,t,j}, cap^{pv}_j, cap^{pvi}_j, cap^{rs}_j, cap^{rsi}_j, g^{pv}_{d,t,j}, ch^{rs}_{d,t,j}, dc^{rs}_{d,t,j}, peak_{m,j}, e^{rs}_{d,t,j}\} \tag{3}$$
$$s.t.\ w^{off}_{d,t,j} - w^{inj}_{d,t,j} = D_{d,t,j} - g^{pv}_{d,t,j} + ch^{rs}_{d,t,j} - dc^{rs}_{d,t,j}, \quad \forall d\in\mathcal{D}, t\in\mathcal{T} \tag{4}$$
$$0 \le g^{pv}_{d,t,j} \le AF^{pv}_{d,t,j} \cdot cap^{pv}_j, \quad \forall d\in\mathcal{D}, t\in\mathcal{T} \tag{5}$$
$$g^{pv}_{d,t,j} \le cap^{pvi}_j, \quad \forall d\in\mathcal{D}, t\in\mathcal{T} \tag{6}$$
$$e^{rs}_{d,t,j} = \delta \cdot e^{rs}_{d,t-1,j} + ch^{rs}_{d,t,j} \cdot \eta^{rs}_{ch} \cdot \eta^{rsi} - dc^{rs}_{d,t,j}/(\eta^{rs}_{dc} \cdot \eta^{rsi}), \quad \forall d\in\mathcal{D}, t\in\mathcal{T}/\{1\} \tag{7}$$
$$e^{rs}_{d,1,j} = \delta \cdot cap^{rs}_j/2 + ch^{rs}_{d,1,j} \cdot \eta^{rs}_{ch} \cdot \eta^{rsi} - dc^{rs}_{d,1,j}/(\eta^{rs}_{dc} \cdot \eta^{rsi}), \quad \forall d\in\mathcal{D} \tag{8}$$
$$e^{rs}_{d,T,j} = cap^{rs}_j/2, \quad \forall d\in\mathcal{D} \tag{9}$$
$$0 \le e^{rs}_{d,t,j} \le cap^{rs}_j, \quad \forall d\in\mathcal{D}, t\in\mathcal{T} \tag{10}$$
$$0 \le ch^{rs}_{d,t,j} \le CR \cdot cap^{rsi}_j, \quad \forall d\in\mathcal{D}, t\in\mathcal{T} \tag{11}$$
$$0 \le dc^{rs}_{d,t,j} \le CR \cdot cap^{rsi}_j, \quad \forall d\in\mathcal{D}, t\in\mathcal{T} \tag{12}$$
$$0 \le w^{inj}_{d,t,j} \le \overline{w^{inj}}, \quad \forall d\in\mathcal{D}, t\in\mathcal{T} \tag{13}$$
$$0 \le w^{off}_{d,t,j} \le \overline{w^{off}}, \quad \forall d\in\mathcal{D}, t\in\mathcal{T} \tag{14}$$
$$0 \le cap^{pv}_j \le \overline{cap^{pv}} \tag{15}$$
$$0 \le cap^{rs}_j \le \overline{cap^{s}} \tag{16}$$
$$peak_{\lceil d/3 \rceil, j} \ge w^{off}_{d,t,j}, \quad \forall d\in\mathcal{D}, t\in\mathcal{T} \tag{17}$$

The behind-the-meter energy balance of each consumer is determined by Constraint (4), which links their hourly net offtake to their demand ($D_{d,t,j}$), the energy charged ($ch^{rs}_{d,t,j}$) or discharged ($dc^{rs}_{d,t,j}$) from their storage system, and the energy produced by their PV system ($g^{PV}_{d,t,j}$). Constraint (5) limits PV generation to the installed capacity adjusted for solar power availability factor ($AF^{pv}_{d,t,j}$). Constraint (6) limits PV production to the capacity of the PV inverter.

Constraints (7)–(12) limit the operation of the battery system. Constraints (7) tracks state-of-charge based on charging and discharging decisions, taking into account self-discharge rate δ and efficiencies η^{rs}_{ch}, η^{rs}_{dc} and η^{rsi}. Cyclic boundary conditions are imposed on the batteries in Constraints (8) and (9). Constraint (10) imposes a limit on the state of charge, which cannot exceed the battery capacity. Constraints (11)–(12) limit the charging and discharging decisions, by the installed capacity multiplied by the charge rate (CR).

Finally, Constraints (13)–(14) emulate connection capacity bounds, imposing physical restrictions on injection and offtake. Constraints (15)–(16) limit consumers' investment in PV and battery respectively. Constraint (17) determines consumers' monthly peak offtakes which are used to calculate distribution costs in capacity tariff cases.

3.4.2. Conventional & renewable generators

The objective of each grid-scale generator (18) is to maximize annual profits, equivalent to operational revenue minus capital expenditure. Generator k decides how much capacity to invest in (cap^{gen}_k) according to annualized investment cost (IC^{gen}_k). Generators also decide, on an hourly basis, how much to generate ($g^{gen}_{d,t,k}$). We assume that renewable generators have a variable operating cost (VC_k) of zero. A generators' decision problem is characterized as the following optimization problem:

$$\max_{x_{k\in\mathcal{K}}} : \sum_{d\in\mathcal{D},t\in\mathcal{T}} \Pi_d \cdot (\lambda_{d,t} - VC_k) \cdot g^{gen}_{d,t,k} - IC^{gen}_k \cdot cap^{gen}_k$$
$$x_k \in \{g^{gen}_{d,t,k}, cap^{gen}_k\} \tag{18}$$
$$s.t.\ 0 \le g^{gen}_{d,t,k} \le AF^{gen}_{d,t,k} \cdot cap^{gen}_k, \quad \forall d\in\mathcal{D}, t\in\mathcal{T} \tag{19}$$

Constraint (19) restricts the generator's hourly production to its installed capacity multiplied by the availability factor ($AF^{gen}_{d,t,k}$). Conventional power plants are assumed to be constantly available at nominal capacity (i.e. have an availability factor always equal to one).

3.4.3. Grid-scale battery operator

The objective of the grid-scale battery operator is to maximize profits (20), equivalent to revenues from discharging minus cost of charging and capital expenditure. The grid-scale battery operator decides how much battery and inverter ($cap^{gs}$and cap^{gsi}) capacity to install according to the annualized investment costs $IC^{gs}$and IC^{gsi}. Decision variables also include the energy stored in the battery ($e^{gs}_{d,t}$), as well as the amount the operator decides to charge ($ch^{gs}_{d,t}$) and discharge ($dc^{gs}_{d,t}$) on an hourly basis. Constraints governing the operation of the grid-scale battery are the same as those of residential BESS. However, we highlight that the grid-scale battery operates within the wholesale market and is subject to wholesale prices. The grid-scale battery operator solves the following optimization problem:

$$\max_{x^{gs}} : \sum_{d\in\mathcal{D},t\in\mathcal{T}} \Pi_d \cdot \lambda_{d,t} \cdot (dc^{gs}_{d,t} - ch^{gs}_{d,t}) - IC^{gs} \cdot cap^{gs} - IC^{gsi} \cdot cap^{gsi}$$
$$x^{gs} \in \{dc^{gs}_{d,t}, ch^{gs}_{d,t}, e^{gs}_{d,t}, cap^{gs}, cap^{gsi}\} \tag{20}$$
$$s.t.\ e^{gs}_{d,t} = \delta \cdot e^{gs}_{d,t-1} + ch^{gs}_{d,t} \cdot (\eta^{gs}_{ch} \cdot \eta^{gsi}) - dc^{gs}_{d,t}/(\eta^{gs}_{dc} \cdot \eta^{gsi}), \quad \forall d\in\mathcal{D}, t\in\mathcal{T}/\{1\} \tag{21}$$
$$e^{gs}_{d,1} = \delta \cdot cap^{gs}/2 + ch^{gs}_{d,1} \cdot (\eta^{gs}_{ch} \cdot \eta^{gsi}) - dc^{gs}_{d,1}/(\eta^{gs}_{dc} \cdot \eta^{gsi}), \quad \forall d\in\mathcal{D} \tag{22}$$
$$e^{gs}_{d,T} = cap^{gs}/2, \quad \forall d\in\mathcal{D} \tag{23}$$
$$0 \le e^{gs}_{d,t} \le cap^{gs}, \quad \forall d\in D, t\in\mathcal{T} \tag{24}$$
$$0 \le ch^{gs}_{d,t} \le CR \cdot cap^{gsi}, \quad \forall d\in\mathcal{D}, t\in\mathcal{T} \tag{25}$$
$$0 \le dc^{gs}_{d,t} \le CR \cdot cap^{gsi}, \quad \forall d\in\mathcal{D}, t\in\mathcal{T} \tag{26}$$

[9] When studying a specific tariff design, two of these values are set to zero.

3.4.4. Market operator

The optimization problems of all agents are coupled through the market clearing constraint, Eq. (27), responsibility of the market operator, which ensures an equilibrium between electricity supply and the sum of residential and non-residential net offtake ($D^{nres}_{d,t}$) in the whole energy system at each time step. The market operator thus sets the wholesale electricity price ($\lambda_{d,t}$) to match demand with supply:

$$\sum_{k\in K} g^{gen}_{d,t,k} + g^{w}_{d,t} + (dc^{gs}_{d,t} - ch^{gs}_{d,t}) = D^{nres}_{d,t} - \sum_{j\in J}(w^{off}_{d,t,j} - w^{inj}_{d,t,j}) \tag{27}$$

3.5. Solution algorithm

The Nash equilibrium of the non-cooperative game is solved by the Alternating Direction Method of Multipliers (ADMM) algorithm, inspired by the implementation of [33,36]. ADMM is a dual decomposition method that was originally developed to solve convex optimization problems by separating them into smaller optimization problems [37]. A brief introduction of how ADMM algorithm works in our model can be found in Appendix A. The model is implemented in Julia [38] using JuMP [39] and solved with Gurobi [40]. All the data utilized in the algorithm is introduced in Section 4. For additional information regarding the code and data used for the case study, we refer interested readers to GitLab repository [41].

4. Case study: data and assumptions

In this section, we introduce the data and assumptions inspired by a potential Belgian system in 2030. In total, we consider ten representative residential consumer types, each having a unique load profile, solar PV load factor and perceived, annualized investment costs.

4.1. DER parameters

All residential consumers are able to invest in solar PV and BESS, with investment limits ($\overline{cap^{pv}}$ and $\overline{cap^{s}}$) set to 10 kW and 14 kWh. These are in line with the maximal size of roof-mounted PV systems for single-family homes in Belgium [42] and a Tesla PowerWall [43] respectively. Solar PV and BESS installations each require an associated inverter. All techno-economic parameters of DER installations are shown in Table 1. The investment costs for solar PV and respective inverter are derived from 2019 solar PV system costs, found in [44] and extrapolated to 2030 using learning rates from [45]. To obtain model inputs PIC^{pv}_j, PIC^{pvi}_j, $PIC^{rs}_j$and PIC^{rsi}_j, investment costs are annualized according to the technology's lifetime and discount rate. The discount rate is randomly assigned to each consumer within a range of 3%–12% to simulate varying degrees of risk aversion. Physical limits on injection and off take are as per Belgian residential connection capacity agreements [46].

4.2. Grid-scale technology parameters

We consider: three types of conventional generators, generalized as base, mid and peak-load technology, a wind farm and a grid-scale battery. The investment cost and variable cost of each technology is listed in Table 2 and are taken from [36]. Additionally, we introduce a relatively low price cap of 500 €/MWh to mimic flexibility that may not be captured in an isolated electricity market, such as industrial demand response and interconnections.

For grid-scale batteries, we utilize the same techno-economic parameters as for residential batteries. The investment cost of grid-scale batteries and their inverters is annualized using a discount rate of 5%. However, we account for economies of scale by assigning a lower inverter investment cost of 46 €/kW and a higher efficiency of 98% compared to residential BESS inverters [47].

Table 1
Techno-economic parameters for residential solar PV and BESS. The data source is shown as either a reference or own model assumption (MA). Listed investment costs are not annualized.

Parameter	Symbol	Unit	Value	Source
Solar PV				
Investment cost		€/kW	540	[44,45]
Lifetime		years	25	[44]
PV Inverter				
Investment cost		€/kW	115	[44,45]
Lifetime		years	15	[44]
BESS				
Investment cost		€/kWh	153	[47]
Lifetime		years	18	[47]
Charge rate	CR		1	MA
Charging efficiency	η^{rs}_{ch}	%	97	[47]
Discharging efficiency	η^{rs}_{dc}	%	97	[47]
Self-discharge	δ	%/hour	99.99	MA
BESS Inverter				
Investment cost		€/kW	56	[47]
Lifetime		years	20	[47]
Efficiency	η^{rsi}	%	95	[47]
Common				
Discount rate		%	3–12	MA

Table 2
Annualized investment cost (IC) and variable cost (VC) of centralized generation technologies.

Technology	IC [€/MWy]	VC [€/MWh]
Base	138 000	36
Mid	82 000	53
Peak	59 000	76
Wind	76 500	0
Grid-scale BESS	13 114	NA
Grid-scale BESS inverter	3723	NA

4.3. Time series

Hourly availability factors for residential solar PV are taken from [48], in which current as well as potential solar electricity generation is mapped for Belgium. Taking into account the variations in geographic location, we assign unique solar availability factors of 10 provinces in Belgium to the 10 categories of residential consumers to reflect the heterogeneity of solar PV generation potential. To delineate the production potential of wind we use the hourly, wind availability factor also found in [48].

Each consumer has an individual, hourly, electricity load $D_{d,t,j}$. We generate 300 load profiles using the open source tool StROBe (Stochastic Residential Occupancy Behavior) [49]. The StROBe tool models residential occupant behavior based on Belgian statistics for a typical weather year, with each profile comprising electricity demand for lighting, large and small appliances as well as electronics. From this pool of profiles, we sample a set of ten representative consumers whose average annual household demand matches the Belgian average (3500 kWh) [50]. We then scale these ten types up to 4.8 million, approximating the total number of Belgian households.

In our model, we also incorporate non-residential load, $D^{nres}_{d,t}$, which is obtained by subtracting the total scaled residential demand of ten representative consumer types from the 2017 Elia Total Load data [51].

4.4. Representative days

We model an entire year with an hourly temporal resolution by representative days in order to maintain computational tractability. Three days are used to represent each month. Thus, a total of 36 weighted representative time series of 24 h are used in this study. The representative days are found according to the optimization problem outlined in [52]. We leverage the Julia package *RepresentativePeriodsFinder.jl* to select representative periods from time series data [53].

4.5. Tariff calibration

We consider three distribution tariff options, namely a volumetric distribution tariff (VOL), a capacity distribution tariff (CAP), and a fixed distribution tariff (FIX), as introduced in Section 3.2. In order to obtain meaningful results when comparing these three options, calibrations are required. Firstly, we select the volumetric distribution tariff as the baseline case, and fix its value to 60.7 €/MWh, i.e. the distribution cost (in the unit of €/MWh) in Flanders in 2022 [54]. This value is then kept constant across all temporal granularities under the VOL tariff. Next, we calculate the total distribution cost (sum of volumetric tariffs paid by all households) in the real-time pricing (H1) case. This cost serves as a benchmark to calibrate the values of both the capacity tariff and fixed tariff in the RTP case, ensuring that the same total distribution cost can be recovered for all three tariff options in the RTP case. Once the tariff values are calibrated, they are fixed and applied to all temporal granularities of retail electricity pricing. It is important to note that the total income of distribution system operators (DSOs) can differ across the varying temporal granularities of retail electricity prices. However, among all the cases examined in our paper, the total DSO income differs by less than 3% in all but one cases. The M12 VOL case stands out with an approximately 9% difference in total DSO income compared to the other cases.

5. Results and discussion

In this section, we describe the results of our case study. Generation capacity investments are covered first in Section 5.1, average retail prices follow in Section 5.2. In Section 5.3 we delve into the market value of residential BESS. In Section 5.4 we look at offtake and injection peaks and in Section 5.5, we provide an explanation for the trends in total system cost. We provide a detailed breakdown of cost components of individual residential consumer bills in Appendix C. In the case study, we utilize stylized electricity prices limited to three levels, primarily due to the assumption of three stylized aggregated conventional power plants. We deem this as the most constraining assumption concerning the parameter values as stylized wholesale prices will potentially also yield stylized retail prices, which may affect the conclusions. To assess the robustness of these results, we additionally explore the integration of more centralized transmission-level technologies. The set-up and results of the analysis are not presented in the main body, but in Appendix E. Generally, our conclusions are robust against the inclusion of multiple generating technologies on the wholesale level.

5.1. Generation capacity investments

We begin our analysis by examining how the temporal granularity of retail electricity prices, in combination with the FIX, CAP or VOL tariff shapes investments in generation capacity. Fig. 3 illustrates the invested capacity of each generation technology across decreasing temporal granularity of retail electricity prices, for the three investigated tariffs.

Total installed capacity is the lowest for the FIX tariff, which is caused by two mechanisms. Firstly, on the residential level, the FIX tariff does not incentivize DER investments while VOL and CAP tariffs do. The VOL tariff incentivizes greater investments in solar PV, while the CAP tariff promotes greater investments in residential BESS. Under the VOL tariff, consumers can mitigate volume-based network costs by installing solar PV for self-consumption. On the other hand, the CAP tariff encourages investments in residential BESS, which help reduce individual peak consumption and consequently alleviate capacity-based network costs. In contrast, the FIX tariff imposes a yearly lump cost, unavoidable by means of DER investments. Secondly, on the wholesale level, energy systems under CAP and VOL tariffs, albeit larger presence of DER, need a similar amount of conventional generation capacity as under the FIX tariff. This is triggered by instances of high demand during which solar and wind availability factors are low. These periods are too vast for storage to make a significant contribution to demand.

Notably, variation in installed generation capacities is greater between the different distribution tariffs than across decreasing temporal granularity of retail prices. No systematic change in total or technology-specific installed generation capacity under a given tariff occurs.

We point, however, to changes in individual consumers' solar PV investments. This can be seen in Fig. 4, which shows individual investments in solar PV capacity.[10] These changes are the result of how offtake and injection prices evolve with decreasing temporal granularity of retail electricity prices. We will elaborate on retail price patterns in Section 5.2, for now, it suffices to understand that injection prices generally decrease and offtake prices generally increase for longer averaging resolutions (Fig. 5).

First note that, perhaps not surprisingly, consumers with lower discount rates tend to invest heavily in PV generation. Crucially, this phenomenon is more pronounced for highly granular pricing resolutions because of the comparatively higher injection prices. Indeed, large installations rely heavily on injection prices to remain competitive, given that their production is often too substantial for immediate consumption. Consequently, as injection prices decrease with lower pricing resolutions, these large installations correspondingly become less profitable and decrease in size up until the increased reliance on self-consumption offsets this loss. Put differently, a relatively larger part of their generation is being valued at offtake prices, which tend to be higher in lower pricing resolutions. Likewise, higher offtake prices provide an incentive for smaller installations to appear or expand in size, as long as a sufficiently large part of their production is being valued at offtake prices, i.e. through self-consumption. Thus, lower pricing resolutions, characterized by lower injection but higher offtake prices, incentivize PV installations to be comparatively smaller and more widely distributed.

5.2. Retail electricity prices

In Fig. 5, we illustrate yearly average offtake and injection prices under each tariff across decreasing temporal granularity of retail electricity prices. The values presented are weighted with respect to offtake and injection, to better represent the average price that consumers face:

$$\overline{\lambda^{off}} = \frac{\sum_{d\in D,t\in T} \Pi_d \cdot \lambda^{off}_{d,t} \cdot Off_{d,t}}{\sum_{d\in D,t\in T} \Pi_d \cdot Off_{d,t}} \tag{28}$$

$$\overline{\lambda^{inj}} = \frac{\sum_{d\in D,t\in T} \Pi_d \cdot \lambda^{inj}_{d,t} \cdot Inj_{d,t}}{\sum_{d\in D,t\in T} \Pi_d \cdot Inj_{d,t}} \tag{29}$$

As the temporal granularity of retail electricity prices decreases, average offtake prices generally increase while average injection prices decrease. To illustrate why, we first note that Eqs. (28)–(29) can be rewritten in function of the wholesale price using Eqs. (1)–(2).[11] Changes to average offtake or injection prices can hence occur because of changes to (i) wholesale market prices and to (ii) offtake or injection patterns, with the latter effect being more dominant. In particular,

[10] We exhibit individual investments in residential BESS capacity in Appendix D.

[11] E.g. the average offtake price reads: $\frac{\sum_{d\in D,t\in T} \Pi_d \cdot \lambda_{d,t} \cdot Off_{d,t}}{\sum_{d\in D,t\in T} \Pi_d \cdot Off_{d,t}}$.

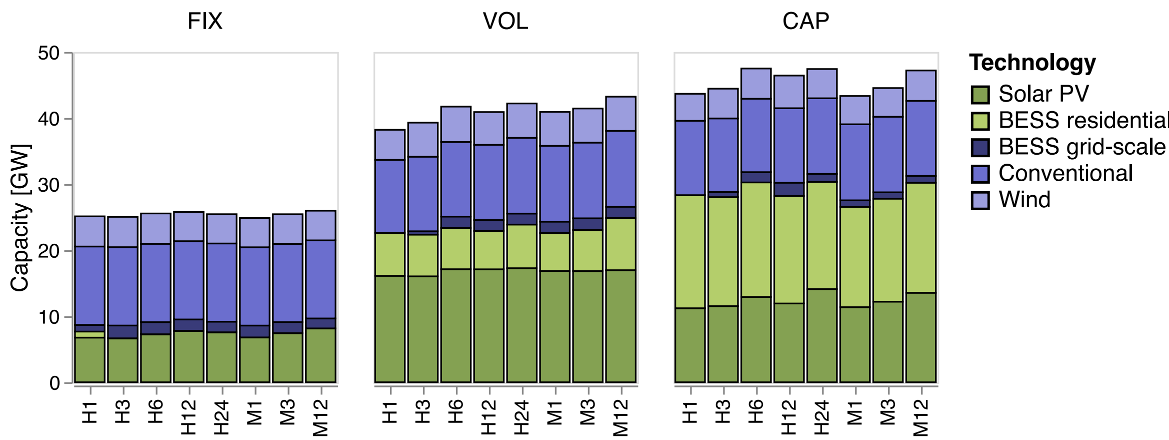

Fig. 3. Generation capacity investments for all considered technologies, under each tariff, across decreasing temporal granularity of retail electricity prices. The depicted solar PV and BESS capacities are the scaled, total capacities installed by all consumers. FIX: fixed tariff, VOL: volumetric tariff, CAP: capacity tariff, H: hourly temporal granularity, M: monthly temporal granularity.

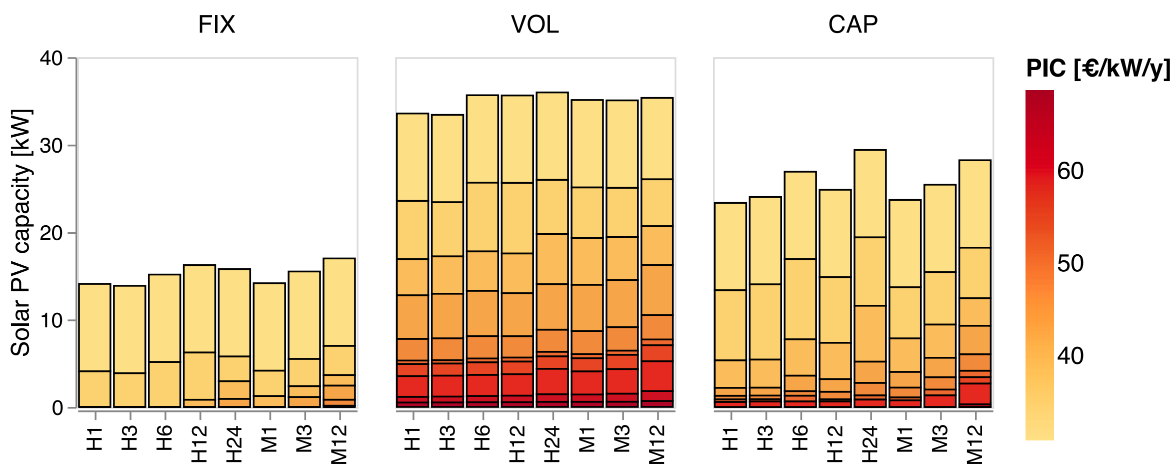

Fig. 4. Installed, individual, consumer solar PV capacities, under each tariff, across decreasing temporal granularity of retail electricity prices. Color scale indicates the perceived annualized investment cost (PIC) and each small block represents investment of each representative consumer. FIX: fixed tariff, VOL: volumetric tariff, CAP: capacity tariff, H: hourly temporal granularity, M: monthly temporal granularity.

there are two[12] main factors altering offtake and injection patterns over our cases: the total amount of solar PV capacity and the operation of residential batteries. In what follows, we cover these in turn.

As discussed in Section 5.1, total installed PV capacity is predominantly driven by the type of distribution tariff. By comparing Figs. 4 and 5, one can note that additional PV capacity indeed depresses the average injection price and increases the average offtake price. PV generation tends to be concentrated during lower wholesale electricity prices and additional PV capacity hence proportionally increases injection during these periods. Low-price periods are then more heavily weighted in the calculation of the average injection price, which in turn decreases. Likewise, additional PV capacity proportionally decreases offtake during low wholesale price periods and increases the average offtake price. Intuitively and thus also when considering the price-averaging effect, additional PV capacity decreases its value for residential consumers.

Fig. 5 additionally illustrates that the average injection (offtake) price decreases (increases) for lower temporal granularities. A first factor to consider here is the operation of battery installations. If operated

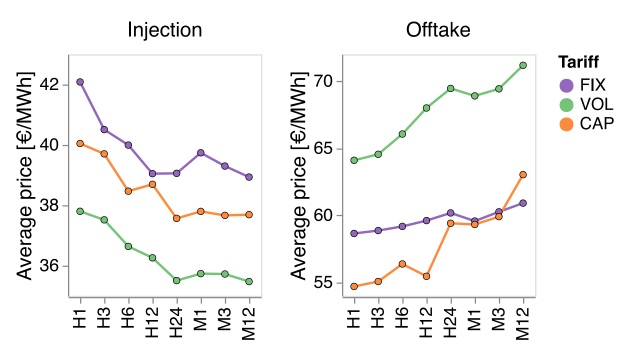

Fig. 5. Average offtake & injection prices under each tariff, across decreasing temporal granularity of retail electricity prices. FIX: fixed tariff, VOL: volumetric tariff, CAP: capacity tariff, H: hourly temporal granularity, M: monthly temporal granularity.

based on wholesale market signals, batteries tend to charge at low prices and discharge at high prices. They should hence increase offtake during low-price periods and decrease offtake during high-price periods (and vice versa for injection). Such operations correspondingly increase injection prices and decrease offtake prices, i.e. batteries smooth out price differentials.

[12] A third but smaller factor concerns the distribution of PV installations as covered in Section 5.1. Generally speaking, longer pricing resolutions tend to promote more distributed PV installations, which in turn tend to increase the average offtake price whilst having an ambiguous effect on the average injection price.

In practice, prosumers adapt their battery operations based on the pricing resolution and the distribution tariff. Lower pricing resolutions (i.e. longer averaging periods) yield a price differential between offtake and injection prices and prosumers will use their batteries to increase the self-consumption from their PV installations. They charge their batteries during periods of ample PV production and consume their stored energy to avoid offtaking from the grid. Crucially, these charging and discharging moments do not necessarily coincide with the lowest or highest wholesale market prices, respectively. This leads to proportionally less offtake (injection) during low-priced (high-priced) hours and hence increases the average offtake price and decreases the average injection price. The more the pricing resolution decreases, the more pronounced this effect becomes as (i) wholesale signals are more concealed and (ii) injection and offtake price differentials increase.

In addition, battery operations may be influenced by the desire to reduce grid tariff expenses. In the volumetric tariff cases, residential consumers pay an extra fee proportional to their grid-supplied electricity consumption. This presents an additional incentive for self-consumption and reinforces the phenomenon mentioned above. For the capacity-based tariff, prosumers also employ their batteries for peak-shaving, i.e. to avoid large offtake peaks. Batteries are operated to charge during off-peak hours and discharge during peak hours, again without any guarantee that these hours coincide with respectively low or high wholesale market prices (even though there is a correlation). Generally, these additional incentives cause battery operations to deviate from the ideal wholesale market perspective. Any such deviations result in increased offtake prices and decreased injection prices. With longer averaging resolutions, prosumers become increasingly detached from wholesale market signals, magnifying this effect.

In summary, the impact on average retail prices can be explained through changes in injection and offtake patterns, influenced primarily by two key factors. First, a higher total PV capacity tends to increase offtake prices and decrease injection prices. Second, longer pricing resolutions and volumetric or capacity-based distribution tariffs alter storage operations which in general also increases offtake prices and decreases injection prices.

5.3. Market value of residential BESS

Under hourly pricing (H1), households are exposed to wholesale price signals and hence set their battery operations to match the system's needs. Lower retail pricing granularities, however, disconnect residential consumers from these signals and their batteries may therefore no longer be operated efficiently. In what follows, we introduce and analyze a metric which quantifies this loss in market value. We remind the reader that under the FIX tariff, for temporal granularities H3 to M12, no residential batteries are installed, thus no metric is shown.

We define the marginal market value of BESS (MV_{BESS}) as the reduction in annual electricity generation costs when adding one additional unit of battery energy capacity. Mathematically, this can be represented by Eq. (30), with $\lambda_{d,t}$ the wholesale price and $ch_{d,t,j}$ and $dc_{d,t,j}$ the charging and discharging operations, respectively. The metric is normalized by accounting for the total installed residential BESS capacity ($\sum_{j\in\mathcal{J}} cap^s_j$).

$$\text{MV}_{BESS} = \sum_{d\in\mathcal{D},t\in\mathcal{T},j\in\mathcal{J}} \left(\Pi_d \cdot (dc_{d,t,j} - ch_{d,t,j}) \cdot \lambda_{d,t} \right) / \sum_{j\in J} (cap^s_j) \tag{30}$$

This metric captures operational inefficiencies of battery operations, but also structural value differences across cases. Indeed, the marginal market value could for instance be lower in cases with excessive BESS capacity because of diminishing returns, and could be higher in cases that exhibit high PV penetration because of additional arbitrage opportunities. We disentangle these effects by additionally evaluating Eq. (30) with optimal charging and discharging operations.[13] As such, we have a benchmark metric that captures the maximally attainable marginal value of battery energy capacity, evaluated at optimal (dis)charging operations; and a metric that captures the realized marginal value, evaluated at (dis)charging operations determined by the residential consumers.

Fig. 6 depicts the benchmark market value of residential BESS operations with gray bars, and the realized value with black horizontal lines. Under hourly pricing with FIX tariff, the realized market value aligns closely with the optimum value, indicating system-optimal BESS operations. However, under the VOL and CAP tariffs, the market values drop to respectively 50% and 30% of the benchmark. This demonstrates that distribution tariffs alter the operational signal embedded in the retail electricity price, precluding BESS operations from aligning with the wholesale market.

As the temporal granularity of retail prices decreases, the realized market value of BESS operations decreases under all tariff schemes. Specifically, under the VOL tariff, the realized market value decreases systematically, even reaching negative values. This indicates that residential BESS operations are misaligned with the price signal in the wholesale electricity market.

The realized market value of residential BESS operations exhibit a more nuanced pattern under the CAP tariff. Across all temporal granularities of retail electricity prices, the realized market values are consistently positive but below 30%. A capacity tariff, which bills households based on their monthly peak offtake, indirectly encourages them to operate their BESS in a system-friendly manner, particularly when their individual peak consumption coincides with the system peak. As a result, the offtake and offtake prices are reduced during these peak hours. However, it is important to note that offtake price peaks at lower temporal granularities of retail prices may not necessarily align with the system peak hours. Consequently, the incentives for households to reduce their individual peak offtake may not consistently result in efficient BESS operations from a market value perspective.

5.4. Grid load

In Fig. 7, we illustrate the maximum yearly injection and offtake under each investigated tariff, across decreasing temporal granularity of retail electricity prices.

Evidently, the CAP tariff, compared to the others, can significantly reduce peak offtake. This reduction can be attributed to the billing of network costs based on households' monthly peak offtake and the resulting larger presence of residential BESS. Despite substantial solar PV capacity triggered by the VOL tariff, the reduction in peak offtake is, on average, 27% less than that achieved under the CAP tariff. This is because most peak offtake occurs during periods of low PV generation. Moreover, significant incentives for solar PV investment under the VOL tariff lead to greater injection, further exacerbating the distribution grid burden. In comparison, the reduced grid interaction resulting from BESS investments and usage under the CAP tariff may provide grid benefits that other tariffs cannot.

There are no systematic trends observed in the grid interaction across decreasing temporal granularity of retail electricity prices. The fluctuations in peak offtake and injection observed across decreasing temporal granularity of retail electricity prices are influenced by various factors such as volatile electricity prices, the demand profile of prosumers, and the non-residential load. In some instances, the operations of residential batteries align with the system's needs and

[13] We obtain these by running an ex-post optimization in which residential battery operations are optimized based on wholesale prices.

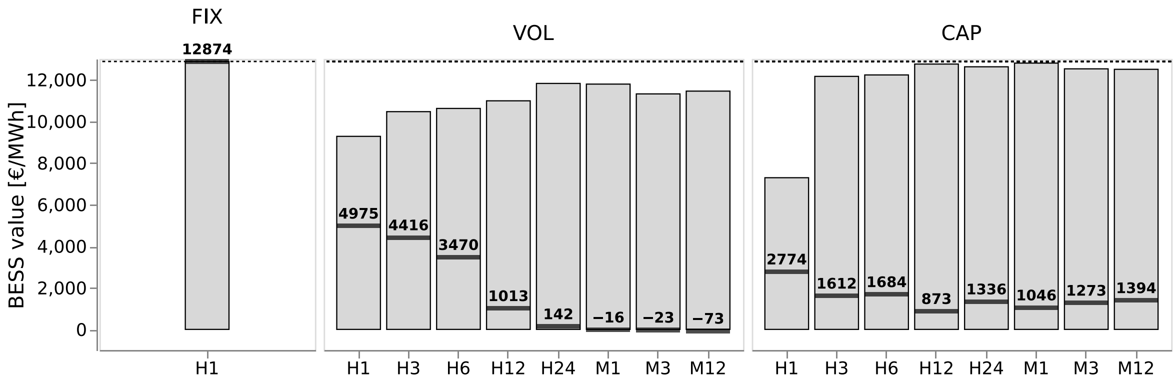

Fig. 6. Market value of residential BESS operations across decreasing temporal granularity of retail electricity prices and tariff types. Benchmark market values depicted by gray bars and the realized market values depicted by horizontal black lines are both calculated by Eq. (30). FIX: fixed tariff, VOL: volumetric tariff, CAP: capacity tariff, H: hourly temporal granularity, M: monthly temporal granularity.

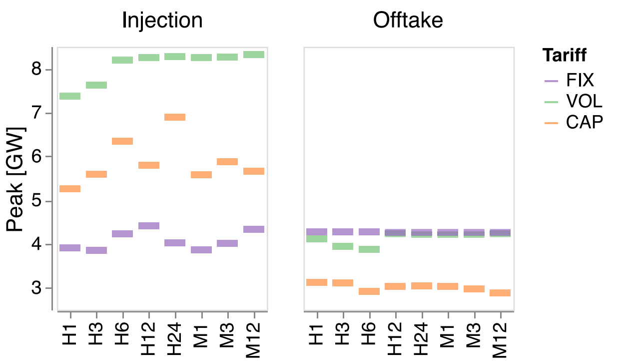

Fig. 7. Annual peak offtake and injection under each tariff, across decreasing temporal granularity for retail electricity prices. FIX: fixed tariff, VOL: volumetric tariff, CAP: capacity tariff, H: hourly temporal granularity, M: monthly temporal granularity.

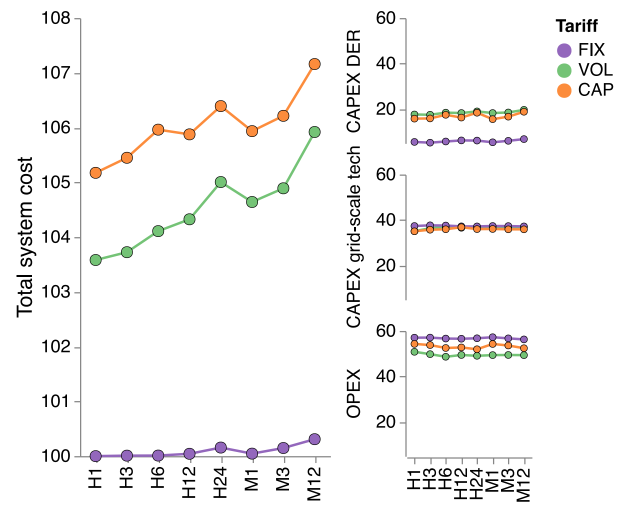

Fig. 8. Total system cost and constituents: CAPEX in DER, CAPEX in grid-scale technologies and OPEX. Costs are normalized using the lowest occurring total system cost: H1 FIX tariff total system cost. FIX: fixed tariff, VOL: volumetric tariff, CAP: capacity tariff, H: hourly temporal granularity, M: monthly temporal granularity.

result in a beneficial reduction in peak offtake. This occurs when battery charging and discharging patterns adjust to the factors mentioned above, mitigating the peak offtake without requiring specific control interventions. However, it is worth mentioning that the peak offtake in the CAP tariff M12 case is the lowest among all cases, indicating that a capacity tariff based on individual peak offtake can effectively reduce the system peak.

5.5. Total system cost

Leveraging prior results, we now turn to the total system cost. In Fig. 8 we illustrate, in the left panel, the normalized total system cost, as well as its constituents, in the right panels: CAPEX in DER, CAPEX in grid-scale technologies and OPEX. Note that the y-axis of the figure starts from 100 as we have normalized the total system cost using the total system cost resulting from the H1 FIX case, i.e. the most optimal outcome in our setting. For further details on total system cost components we refer interested readers to Appendix B.

We first note that the difference in total system cost is greater between distribution tariffs than when moving across decreasing temporal granularity of retail prices. The FIX tariff exhibits the lowest total system cost,[14] which links back to our discussion on generation capacity investments. The FIX tariff, compared to the CAP and VOL tariffs, promotes significantly lower investments in DER, the main driver for the cost difference as can be seen in Fig. 8. The difference in total system cost between the VOL and CAP tariffs can be attributed to a reduced OPEX under a volume-based tariff. The VOL tariff, promotes greater solar PV investment, resulting in higher levels of distributed generation, therefore requiring overall less generation of conventional technologies throughout the year.

The second finding is that the total system cost increases with a decreasing temporal retail pricing granularity. This is caused by a less cost-efficient generation mix, exacerbated by less efficient residential BESS operations, as explained in Section 5.3. Since the CAP and VOL tariffs include both more solar PV and residential BESS than the FIX tariff, decreasing temporal granularity of retail electricity prices has a more influential effect on total system cost, as can be seen by the steeper slopes in Fig. 8. This makes the problems worse when dealing with cases with low temporal granularities. For instance, the transition from H1 to M12 in FIX tariff cases shows hardly any difference, while the shift from H1 to M12 in VOL tariff cases results in a 2-percentage point difference, highlighting the impact of distribution tariffs.

Fig. 9 illustrates in more detail how expenditures in each technology changes, relative to hourly pricing. We have already highlighted the redistribution of solar PV installations for lower pricing granularities (see Section 5.2), which entails more expensive solar PV

[14] This result is limited by our assumption that all network costs are residual or sunk. A valid assumption in networks experiencing low load growth, with minor changes in network capacity needs, having most of the dimensioning costs occurred in the past. Note, however, that literature suggests capacity-based charges can lead to the lowest system cost if network investments are not sunk [2].

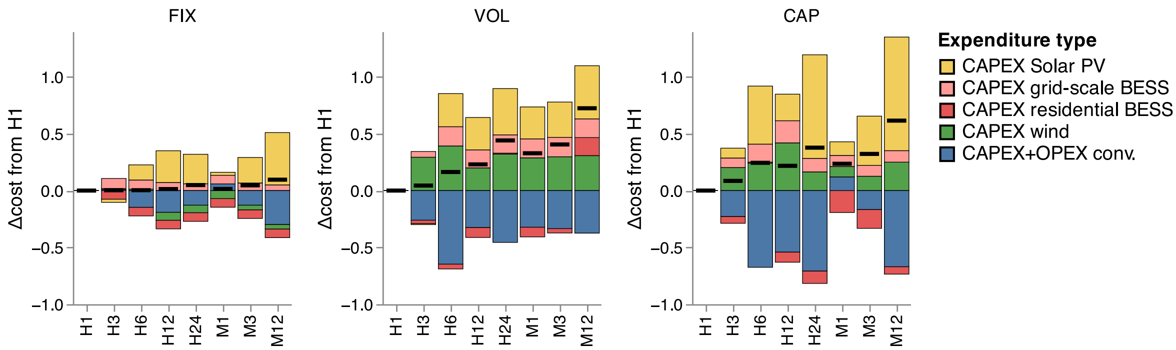

Fig. 9. Normalized change in expenditure of each technology relative to H1 granularity under each tariff, across decreasing temporal granularity of retail electricity prices. Horizontal bars in black illustrate the total increase in cost. FIX: fixed tariff, VOL: volumetric tariff, CAP: capacity tariff, H: hourly temporal granularity, M: monthly temporal granularity.

capacity. By linking wholesale and retail levels, we are able to describe the repercussions of residential investment decisions on transmission-level technologies. With increasingly self-consumption-oriented solar PV installations, expenditure in conventional generation technologies slightly decreases but not to the point of offsetting the additional cost. Additional investments in wind and BESS capacity are, moreover, made at the transmission level. Overall, such adjustments entail a less efficient generation mix, leading to a higher total system cost as the temporal granularity of retail electricity prices decreases. However, it is important to note that transitioning to temporal granularity of H3 (or H6 in the FIX tariff case) can be a valuable alternative to RTP. H3 (H6) is more practical for system operator to implement and for residential consumers to follow compared to RTP. At the same time, it aligns consumer decisions with the system requirements and approximates the welfare benefits of RTP.

We find that the difference in total system cost between a flat retail price (M12) and RTP (H1) is, as put by Borenstein [55] "significant and sobering". Our analysis suggests that the sobering difference can be attributed to the limited reduction in the cost of conventional generation capacity at the transmission level with more granular pricing, aligning with [56]. This may be due to extended periods of low renewable generation and the relatively low cost of maintaining substantial generation capacity, even when it is rarely used [55]. Previous research by Holland and Mansur [19] found that shifting from annual to monthly flat rates could capture about 30% of efficiency gains in the short term. In our results too, it is evident that in simply moving from M12 to M1 a significant portion of the benefits may be captured. Furthermore, Holland and Mansur [19], found that TOU rates can capture 15%–30% of the efficiency gains of RTP, while Borenstein [18] estimated that TOU can capture approximately one-fifth of the efficiency gains of RTP in the long run. If we relate our H6–H12 temporal granularities for retail electricity pricing to TOU rates, we note that the captured benefits are significantly smaller. This is because we allow the wholesale system to adapt to retail-level changes, yielding a more realistic outcome.

6. Conclusion

Increasing the temporal granularity of retail electricity prices can better align consumer decisions with the power system's requirements. Regulated bill components such as distribution tariffs, however, affect electricity price signals. This study offers a quantitative comparison of a wide spectrum of temporal granularities for retail electricity prices in a fully integrated system, whilst considering the interplay with distribution tariffs. Our research stands out by examining alternative pricing schemes that have been overlooked in prior studies. We highlight the significance of evaluating temporal granularity options that could improve upon the approximation of economic efficiency of RTP compared to commonly used schemes, while mitigating some practical disadvantages of RTP, such as difficulty of implementation, unpredictability and the challenge of consumer adaptability to hourly price signals. We model investment as well as operational decisions of an energy system comprising both wholesale and retail levels. Our analysis demonstrates how the temporal granularity of retail electricity prices and distribution tariff design impact DER investment, BESS operation and the power system at large.

Findings illustrate that a decreasing temporal granularity of retail electricity prices leads to an increase in offtake prices and a decrease in injection prices. This is accompanied by a shift from rather centralized to more distributed PV installations. To the authors' knowledge, this is the first time that such an effect has been demonstrated. Distribution tariffs affect the magnitude of retail prices because of the level and type of DER investments they trigger. As reflected in the literature, volumetric tariffs incentivize solar PV investments and capacity-based tariffs trigger investments in BESS [22]. Correspondingly, a volumetric distribution tariff yields the highest offtake prices while a capacity-based distribution tariff yields the lowest.

Similar to [29], we note that volumetric and capacity-based distribution tariffs erode electricity price signals and prevent full wholesale market integration. Fixed distribution tariffs hence lead to the lowest system cost in our case study. Note, however, that these results hinge on our assumptions about ample distribution grid capacity and sunk distribution network cost. In practice, distribution network cost may rise due to substantial injection peaks resulting from incentivized abundant solar PV investment, particularly volumetric tariffs. Total system cost increases with decreasing temporal granularity of retail electricity prices. This is because of a less cost-effective generation mix triggered by rearranged PV installations, and because residential batteries are being operated sub-optimally. While addressing the challenges of RTP, it is worth considering that using a three-hourly or even six-hourly price granularity can be a valuable alternative if one is willing to accept minor economic efficiency losses. Moreover, since we consider the power system at large and allow for interactions between the wholesale and retail levels, we find that gains from RTP are not as significant as those found in the literature. Indeed, part of the inefficiencies of averaged retail prices could be mitigated by adjusting investments and operations on the wholesale level.

We study operational and investment decisions under the assumption of predictable conditions, particularly concerning demand and renewable generation. Future work could, rather than modeling demand and availability factors as fixed time-series, adopt a stochastic framework. With the inclusion of uncertainty, modelers will need to make assumptions on how and when prices are formed and to what extent they internalize this uncertainty. Our paper focuses on a deterministic setting to maintain generality. Future work can extend this paper by considering uncertainty along with specific pricing mechanisms to cope with it.

CRediT authorship contribution statement

Yucun Lu: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Chiara Gorrasi:** Writing – review & editing, Writing – original draft, Visualization, Formal analysis, Data curation, Conceptualization. **Jelle Meus:** Writing – review & editing, Methodology, Conceptualization. **Kenneth Bruninx:** Writing – review & editing, Conceptualization. **Erik Delarue:** Writing – review & editing, Supervision.

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.

Data availability

The data/code is shared with a GitLab repository cited in the paper.

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Appendix A. ADMM

Here is a brief introduction of the ADMM algorithm in long term energy market equilibrium problems. An overview of the algorithm structure is presented in Algorithm 1, and the detailed implementations can be found in GitLab repository [41].

In the algorithm, we begin by defining penalty rates for the wholesale and retail levels (ρ_w, ρ_r), tolerances for the primal and dual residuals (ϵ_{mc}, ϵ_{dual}), and the maximum number of iterations ($iter_{max}$). We initialize the convergence situation and the price variables $\lambda_{d,t}$, which represent the wholesale market prices associated with the coupling constraints. These prices are iteratively updated to guide the agents towards an equilibrium. In each iteration, the updated prices are provided to all agents, who optimize their objective functions accordingly, as described in Section 3.4. Once all agents have solved their optimization problems, we verify the system equilibrium by checking the primal residuals, which capture the imbalances on the coupling constraints. The primal residuals are calculated using the market clearing constraints in Eq. (27), by subtracting the total net offtake from the total production. Additionally, we calculate the dual residuals by comparing the differences between the current production or offtake values and those from the previous iteration. If the coupling constraints are not satisfied, the prices are updated based on the primal residuals. The algorithm continues iterating until it converges, meaning that the solution simultaneously satisfies both the coupling constraints ($\|r_{mc}\| \leq \epsilon_{mc}$) and the optimization problems of each agent ($\|r_{dual}\| \leq \epsilon_{dual}$).

The convergence of the algorithm represents a Nash equilibrium of the game described by Eqs. (3)–(26), which can be further validated by checking the Karush–Kuhn–Tucker (KKT) conditions of all agents' problems.

Algorithm 1: ADMM algorithm for computing a Nash equilibrium of the non-cooperative game

Data: All parameters belonging to all agents' optimization problems.
Result: Nash equilibrium solution to the game.
Define ρ_w, ρ_r , ϵ_{mc}, ϵ_{dual}, $iter_{max}$; Initialize wholesale market price $\lambda_{d,t}$, and $convergence = 0$
while $convergence = False$ **and** $iter \leq iter_{max}$ **do**
  Solve problems of each transmission level technology;
  Solve 10 representative consumers' problems.
  Calculate primal residuals r_{mc} and dual residuals r_{dual}.
  Update wholesale prices: $\lambda = \lambda - \rho_w \cdot r_{mc}$, and then update offtake and injection prices using Eqs. (1) - (2).
  Update convergence:
  $convergence = (\|r_{mc}\| \leq \epsilon_{mc}) \cdot (\|r_{dual}\| \leq \epsilon_{dual})$.
  $iter = iter + 1$.
end

Appendix B. Total system cost components

As shown in Eq. (B.1), total system cost can be broken down into three constituents.

1. CAPEX in DERs: all household investments in solar PV, BESS, and associated inverters (B.2).
2. CAPEX in grid-scale technologies: all investments in capacity of large-scale generators (renewable and conventional) as well as grid-scale BESS plus associated inverter (B.3).
3. OPEX: the variable cost of running (conventional) technologies (B.4).

$$\begin{aligned}\text{Total system cost} = {} & \text{CAPEX DER} \\ & + \text{CAPEX grid-scale technologies} \\ & + \text{OPEX}\end{aligned} \tag{B.1}$$

$$\begin{aligned}\text{CAPEX DER} = {} & \sum_{j\in\mathcal{J}} \Big(PIC_j^{pv} \cdot cap_j^{pv} + PIC_j^{pvi} \cdot cap_j^{pvi} \\ & + PIC_j^{rs} \cdot cap_j^{rs} + PIC_j^{rsi} \cdot cap_j^{rsi} \Big)\end{aligned} \tag{B.2}$$

$$\begin{aligned}\text{CAPEX grid-scale tech} = {} & \sum_{k\in\mathcal{K}} \Big(IC_k^{gen} \cdot cap_k^{gen} \Big) \\ & + IC^{gs} \cdot cap^{gs} + IC^{gsi} \cdot cap^{gsi}\end{aligned} \tag{B.3}$$

$$\text{OPEX} = \sum_{k\in\mathcal{K}} \sum_{d\in D} \sum_{t\in\mathcal{T}} \Big(\Pi_d \cdot VC_k \cdot g_{d,t,k}^{gen} \Big) \tag{B.4}$$

Appendix C. Residential consumer expenses

The expenses of the 10 representative consumers, arranged in ascending order based on their discount rates, are shown in Fig. C.1. The figure reveals several important observations, some of which have already been discussed earlier in Section 5.

1. Prosumers with a low discount rate tend to make significant investments to reduce electricity bills. They can also make a profit from the injection of solar power generation.
2. Investments made by prosumers with a high discount rate are primarily driven by the offtake price and tariffs. As granularity decreases, the increase in the electricity costs encourages their investments.
3. Low temporal granularity of retail electricity prices can indeed incentivize inefficient investments. As granularity decreases, consumers may face higher offtake prices during specific periods. In response, some consumers, even those with high discount

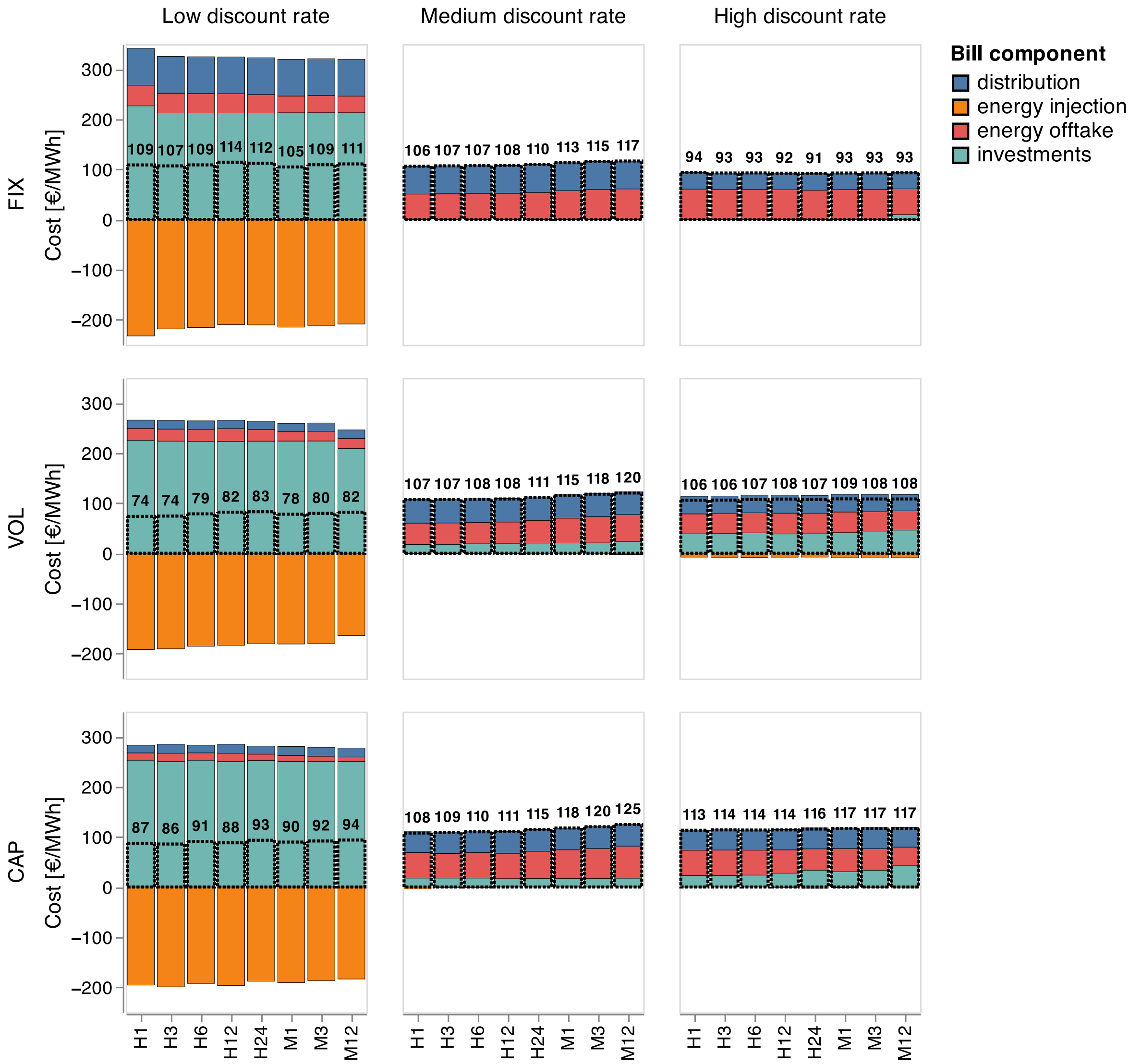

Fig. C.1. Electricity bill of three selected consumers (columns), having low, medium and high solar PV investment costs under each tariff type (rows) across decreasing price granularity. Bill components are color-coordinated. Total bill is illustrated using dashed bars with amount, in €/MWh, written above.

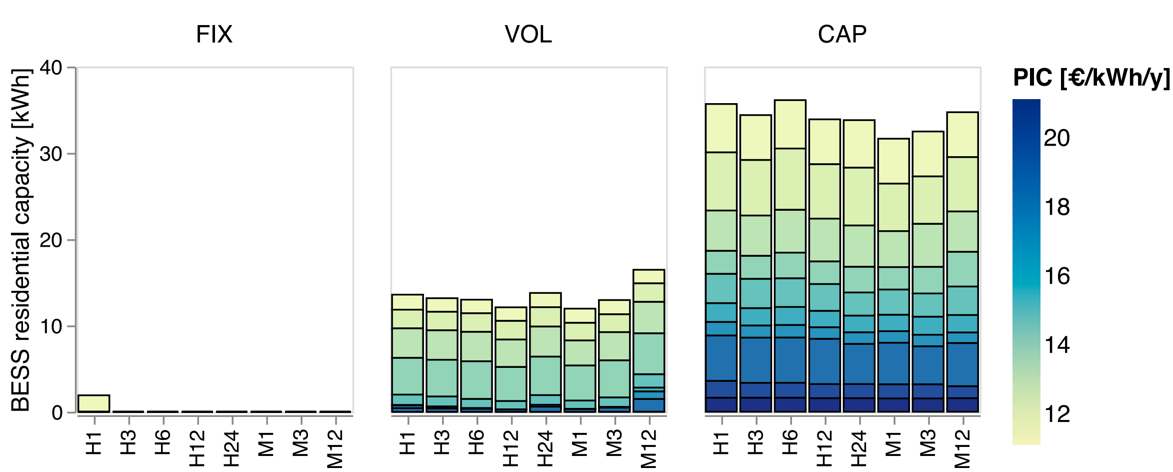

Fig. D.2. Installed consumer BESS capacities, under each tariff, across decreasing temporal granularity of retail electricity prices. Color scale indicates the perceived annualized investment cost (PIC). FIX: fixed tariff, VOL: volumetric tariff, CAP: capacity tariff, H: hourly temporal granularity, M: monthly temporal granularity.

rates, may be motivated to invest in DER to reduce their electricity consumption and lower their bills, as seen in Fig. C.1. However, this behavior may not always result in economically efficient outcomes for the overall energy system.
4. The impact of decreasing injection prices on prosumer investments can be observed from prosumers with low PV investment costs in the FIX tariff cases. As injection prices decrease with decreasing temporal granularity, prosumers who can benefit from high injection prices are discouraged from making large solar PV investments.

Appendix D. Residential BESS installations

In Fig. D.2, it is possible to see the capacities of residential BESS installations under each tariff, for each temporal granularity of retail electricity pricing.

Appendix E. Sensitivity analysis

We conduct one sensitivity analysis by incorporating additional generation technologies at the transmission level. The investment cost and variable cost of all technologies used in the sensitivity analysis are listed in Table E.1. In summary, the total system cost decreases by approximately 2%–3% with the inclusion of more centralized technologies. However, the overall findings and conclusions in Section 5 remain consistent and can still be observed in the figures below (see Figs. E.3–E.7).

Table E.1
Annualized investment cost (IC) and variable cost (VC) of centralized generation technologies.

Technology	IC [€/MWy]	VC [€/MWh]
Base1	138 000	36
Base2	100 000	45
Mid1	82 000	53
Mid2	65 000	65
Peak1	59 000	76
Peak2	53 000	100
Wind	76 500	0

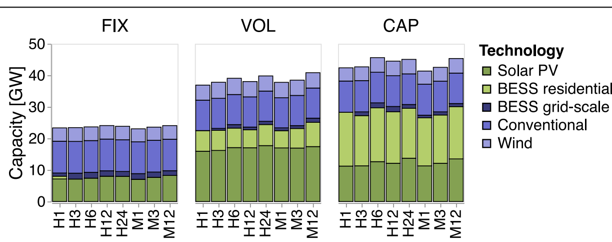

Fig. E.3. Sensitivity analysis results: generation capacity investments for all considered technologies.

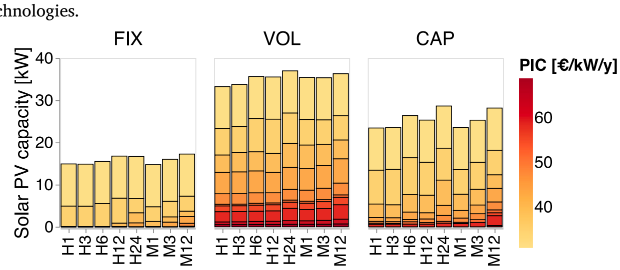

Fig. E.4. Sensitivity analysis results: installed individual consumer solar PV capacities.

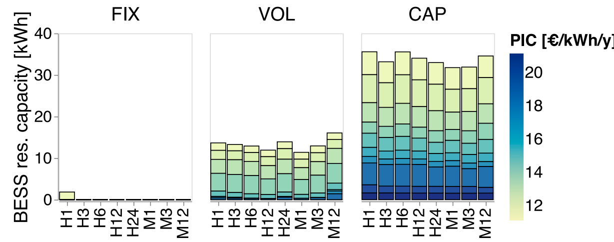

Fig. E.5. Sensitivity analysis results: installed individual consumer BESS capacities.

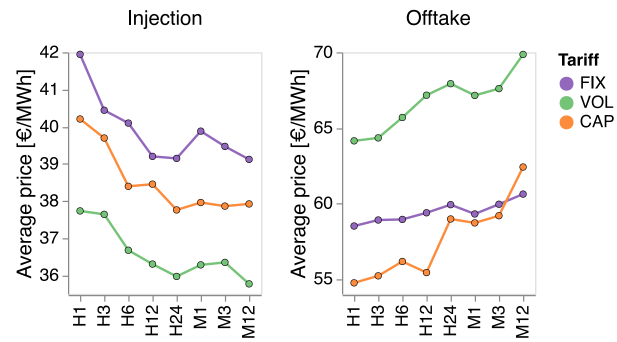

Fig. E.6. Sensitivity analysis results: Average offtake & injection prices.

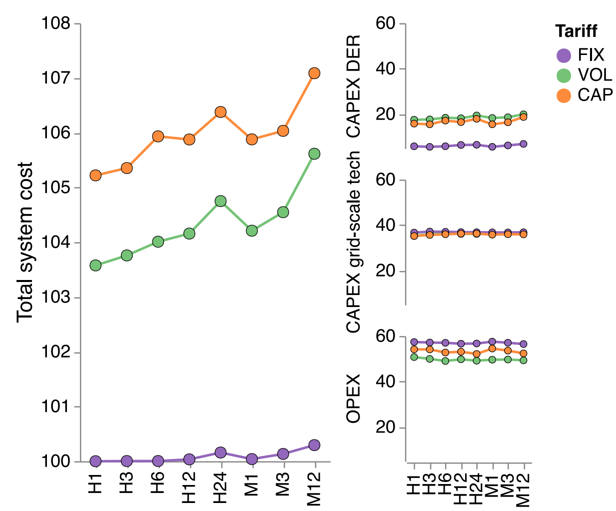

Fig. E.7. Total system cost and constituents. Costs are all normalized using the lowest occurring total system cost: H1 FIX tariff total system cost.

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