A Forward Energy Market to Improve Reliability and Resiliency*

Peter Cramton[†1,3,4], Simon Brandkamp[1,2], Jason Dark[3], Darrell Hoy[3], David Malec[3,4], Axel Ockenfels[1,2], and Chris Wilkens[3]

[1]Max Planck Institute for Research on Collective Goods, Bonn
[2]University of Cologne
[3]Forward Market Design
[4]University of Maryland

2025-03-11

Abstract

We propose a forward electricity market design that enables efficient and granular hedging in the face of growing electrification and intermittent renewables. Market participants can trade thousands of forward contracts and European call options with a high strike price (e.g., $1,000/MWh), each tailored to granular delivery windows spanning up to four years ahead. To implement this market, we apply Budish et al.'s (2023) flow trading framework to electricity markets. It encourages incremental trading and supports liquidity provision via frequent batch auctions. To illustrate our design, we develop a twelve-year simulation of ERCOT's day-ahead market from 2011 to 2022. We derive demand curves for forwards and options for representative generators and load-serving entities. Our analysis reveals that risk preferences significantly shape these demand curves. Risk preferences determine the price-elasticity of demand for forwards and options and influence to what extend market-clearing prices exceed arbitrage-free levels. Moreover, we find that setting a higher option strike price reduces arbitrage positions and makes options less attractive relative to forwards.

*This research is funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under Germany's Excellence Strategy – EXC 2126/1-390838866. This paper is build on and extends a policy-oriented white paper, that we published under the same name and that can be found under Cramton et al. (2024).

[†]Corresponding author: cramton@umd.edu.

1 Introduction

As the world transitions to net zero, nearly all sectors must be electrified, causing the electricity sector to double over the next three decades and spurring rapid innovation in both supply and demand. With an increasing share of intermittent renewables and more frequent extreme weather, balancing supply and demand every second becomes more challenging. A transparent and efficient forward energy market is needed to provide robust price signals for guiding investment and operating decisions consistent with the maximization of social welfare (Cramton, 2017).

Existing forward energy markets are inefficient since they suffer from a lack of liquidity, leading to unreliable forward price signals. This hinders generation companies and load-serving entities (LSEs) from making efficient operational and investment decisions and complicates risk management in day-ahead and real-time markets. Additionally, existing forward and option contracts feature broad delivery periods that do not align with actual load and generation patterns, limiting their effectiveness as hedging instruments. Insufficient hedging leaves participants vulnerable to extreme events like the 2021 Texas winter storm or the 2001 Californian electricity crisis and can lead to bankruptcies and market failures (Borenstein (2002), Cramton (2022)).

In this paper, we propose a novel market design for forward electricity. Participants can trade forward contracts and European call options with a high strike price, e.g., \$1,000/MWh. At any point in time, agents can trade thousands of these derivative products with granular delivery periods for every combination of year-month-hour-weekend/weekday up to four years ahead. For example, a monthly product could cover weekdays 8-9 am in August 2018. Daily products for each day-hour combination are also available for the next 30 days ahead. These granular products allow market participants to choose hedge positions that closely follow their load profiles.

We employ the new flow trading technology by Budish et al. (2023) to enable market participants to trade such a large number of granular products. Flow trading makes it easy and computationally feasible to trade numerous products simultaneously. It also incentivizes gradual, small-quantity trades in hourly frequent batch auctions (Budish et al., 2015). Gradual trade guarantees a constant flow of liquidity, mitigates averse price impact caused by large orders, and reduces opportunities to exercise market power (Budish et al., 2023).

As a proof of concept, we develop a full-scale twelve-year simulation of Texas's ERCOT market between 2011 and 2022. ERCOT provides an interesting case study because it has state-of-the-art day-ahead and real-time markets that send reliable short-term price signals with high scarcity prices up to \$9,000/MWh. These scarcity prices can cause

enormous downside risks, especially for LSEs.

We simulate ERCOT's day-ahead market using the regime-switching model developed by Coulon et al. (2013) and Brandkamp et al. (2025). The regime-switching model simulates joint hourly distributions of day-ahead prices, net load, and gas prices. Generation profiles for multiple solar and wind farms are simulated following Brandkamp et al. (2025). We then apply Mann et al.'s (2017) merit order dispatch model to calculate hourly dispatch and profits for a large sample of 655 existing power plants that operate in ERCOT. We group these power plants into representative generation portfolios. Moreover, we simulate profits for a set of representative load-serving entities (LSEs) that serve a certain share of aggregate load (Brandkamp et al., 2025).

For each representative generator and LSE, we calculate their net demand curves[1] for each granular forward and option product. We obtain agents net demand curves by numerically deriving the optimal quantities of forwards and options for a given pair of forward and option prices. A pair of option and forward quantities is called optimal if it maximizes the agent's expected utility from profits for given prices. We assume agents to be risk-averse with constant absolute risk aversion utility.

Our research aims to use these net demand curves and the flow trading methodology to determine unique market clearing prices and quantities in each hourly frequent batch auction between 2011 and 2022. In this framework we intend to analyze how equilibrium prices and quantities evolve as they approach their physical delivery periods. We also explore how and why market clearing prices differ from arbitrage-free price levels. In addition, we want to study how agents' risk aversion affects market equilibria and net demand for forwards and options. Finally, we investigate how the forward energy market impacts generators and LSEs expected profit, profit volatility, and downside tail risks.

In the current version of our paper, we focus on an analysis of generators and LSE's net demand curves. Our main finding is that agent's risk preferences strongly impact the slope of their net demand curves. When generators and LSE's are highly risk averse, net demand curves are almost vertical since agents are hardly willing to take risks to exploit arbitrage opportunities. The generator is more willing to arbitrage even for high risk levels, because the generator faces less extreme downside risks in the day-ahead market than the LSE (Brandkamp et al., 2025). However, since demand curves are almost vertical for highly risk-averse agents, forward and option prices need to be substantially above their arbitrage-free levels to allow the market to clear.

When agents are less risk-averse, their appetite for arbitrage increases. In particular, the generators' net demand curve becomes less vertical. For reasonably low risk-aversion

[1]Net demand is demand minus supply. A net demand curve gives the net demand for each product as a function of the product prices.

levels, the market will, therefore, likely clear at prices that deviate less than 10% from their arbitrage-free levels.

When generator's and LSEs are nearly risk neutral, our model results in enormous arbitrage positions. Such large arbitrage positions seem unrealistic since participants in real-world derivatives market face collateral requirements that still need to be incorporated into our model.

We also study the price-elasticity of net demand for forwards and options. Notably, net demand for both forwards and options is more sensitive to changes in forward prices than option prices. Net demand is also more elastic to negative biases in the forward price than to positive ones, especially in delivery periods with large day-ahead price spikes. Positive forward price biases encourage agents to take a short position in forwards. Such a short position can lead to extremely large losses when day-ahead price spikes occur. Therefore, agents require a larger price compensation for increasing their short position compared to increasing their long position.

Additionally, we reveal that agents take larger arbitrage positions in peak delivery periods with large price spikes than in off-peak periods with small and rare price spikes. Arbitrage is more lucrative when large price spikes occur. In off-peak periods, net demand curves for forwards and options become almost vertical in the option price. The reason is that the option price is tiny compared to the forward price because an option with a strike price of $\$1,000$/MWh is hardly every in the money in in the off-peak periods. Therefore, changes in the tiny option price are almost irrelevant for net demand.

Finally, we examine how net demand curves change if we choose a lower option strike price of \$200/MWh. Overall, a lower strike price induces agents to take larger option positions and smaller forward positions. With a lower strike price, the option becomes more valuable as it protects agents againts moderate price spikes as Brandkamp et al. (2025) also demonstrate for arbitrage-free prices. In addition, we show that a lower strike price encourages agents to take larger arbitrage positions compared to a higher $\$1,000$/MWh strike price.

In the next section, we relate our paper to the literature on forward market design. Section 3, describes our proposed forward market design and summarizes Budish et al.'s (2023) flow trading approach. Section 4 presents our simulation of ERCOT's day-ahead market and calculates day-ahead profits for representative generators and LSE's. In section 5, we derive net demand curves for these representative agents and sketch suitable trading strategies in the forward energy market. Section 6, presents simulation results and analyzes agents' net demand curves and substitution behavior between forwards and options. Section 7 reflects on the political implications of our novel market design. Section 8 concludes.

2 Related literature

Forward energy markets enhance efficiency by strengthening generators' incentives for competitive bidding in short-term markets (Allaz and Vila, 1993) and by enabling participants to hedge price and quantity risks. However, existing forward markets face significant challenges. Two most prominent challenges are illiquidity and market incompleteness, or the limited number of available products.

Indeed, many forward markets suffer from low liquidity, particularly for contracts beyond one year (Newbery (2016), Genoese et al. (2016)). Illiquidity leads to high price premia and unreliable price signals as Redl et al. (2009) reveal. Illiquid markets might also make it impossible for load-serving entities (LSEs) to hedge sufficiently to be resilient against extreme weather events. Insufficient hedging on the demand side can lead to bankruptcies and market failures, as seen in the 2001 California electricity crisis and the 2022 European energy crisis (Borenstein (2002), Joskow (2008), Cramton (2022)).

Additionally, illiquid forward markets fail to support generators in managing risks from long-term investments. Liquidity for contracts beyond three years rapidly drops to zero (Keppler et al., 2023), discouraging investment in capital-intensive generation assets with long amortization periods. This challenge is particularly relevant for capital-heavy solar and wind assets. Effective hedging can lower the cost of capital for these assets (Genoese et al., 2016).

Another shortcoming of existing forward markets is that they offer only a small number of broad derivative products with monthly, quarterly or yearly delivery periods for base and peak load. These broad products fail to account for the seasonal and daily patterns of generators and LSEs' load.

To address the above shortcomings, researchers and regulators propose several market design innovations. One approach is offering more granular hedge products for specific clusters of hours. Granular products make risk management more effective as they align hedge positions with seasonal and diurnal load and generation patterns (Borenstein (2007), Boroumand et al. (2015), Wolak (2022), Brandkamp (2025)). However, granular products require complex trading strategies and may further fragment liquidity – at least under the existing trading rules.

An alternative solution are load-following forward contracts, used in some U.S. and Australian markets. The seller of the forward contract agrees to supply a fraction of the buyers realized demand in every hour of the contract period (Brown and Sappington, 2023). Load-following forward contracts facilitate risk management as they align hedges with load patterns. However, load-following contracts raise average wholesale prices and reduce welfare because they discourage generators to bid aggressively in day-ahead mar-

kets when demand is low as Brown and Sappington (2023) highlight.

Addressing the lack of liquidity, regulators often mandate generators or LSEs to sell or buy a share of their load forward (de Frutos and Fabra (2012), Wolak (2022)). In our proposal, we also include mandatory purchase obligations for LSEs to foster liquidity and coordinate trade.

However, mandatory forward obligations alone are not sufficient to guarantee liquidity and reliable price signals. For instance, the Australian electricity market has established mandatory purchase obligations, but does not provide LSEs with sufficient means for satisfying these requirements. Many LSEs, especially small retailers, have had trouble finding counterparties for mandated contracting at reasonable and stable prices (ACCC, 2023).

Another proposal is for regulators to purchase long-term electricity contracts via contracts-for-difference (Schlecht et al. (2023), Fabra (2023)). The regulator's role is to provide liquidity and to reduce risk by offering a reliable counterparty. These authors envision that the regulator should purchase the long-term contracts via big-event auctions. They acknowledge that these auctions might suffer from lack of competition and market power (Schlecht et al. (2023), Fabra (2023)). Schlecht et al. (2023) also emphasize that regulator-backed long-term contracts for generators might mute demand response if the regulator does not pass on short-term electricity prices to the demand side.

Our proposal takes a different approach to address the above shortcomings. Our core innovation is to enable market participants to trade thousands of granular products gradually over time. This approach ensures liquidity and reliable price signals while allowing market participants to hedge seasonal and diurnal load variations effectively. As discussed below, some elements of our framework have been developed in earlier studies, especially in research focusing on financial markets. We see our contribution in combining these elements and tailoring them to the unique characteristics of electricity markets.

To make gradual trade of many granular products possible, we apply the flow trading methodology developed by Budish et al. (2023) to electricity markets. Flow trading builds on three principles: 1) Trade gradually in frequent batch auctions, 2) bundle traded products in portfolios, 3) express preferences over portfolios as piecewise linear demand curves. As opposed to many financial markets which are continuous in time while clearing discrete quantities, the flow-trading approach relies on a discrete timing (the frequent batch auctions) and trade continuous quantities (Budish et al., 2023).

It has long been established that trading gradually over time enhances market efficiency since it allows market participants to minimize adverse price impact (Black (1971), Kyle (1985), Vayanos (1999)). Gradual trade is executed in frequent batch auctions that discretize trading to avoid a wasteful arms race for trading speed (Budish et al., 2015). Graf

et al. (2024) provide evidence that frequent batch auctions also raise liquidity in electricity markets compared to continuous trade. Kyle and Lee (2017) argue that agents should express their preferences as piece-wise linear demand curves since piece-wise linear demand guarantees the existence of market clearing prices and makes finding these prices computationally fast (Budish et al., 2023). Portfolio trading allows arbitrage among correlated assets and reflects substitution or complementarity between them, as is known from the combinatorial auctions literature (Budish et al., 2023).

Leveraging the power of flow trading, our forward energy market enables participants to trade thousands of time- and location-specific derivatives gradually. Our approach is closest to Wolak's (2022) Standardized Fixed Price Forward Contact (SFPFC) mechanism, which proposes granular hourly forward contracts. The main difference is that Wolak (2022) envisions SFPFCs to be traded in big-event auctions while we propose gradual trade over time. Big event auctions allow market participants to exercise market power and make it more difficult to manage price risk than under gradual trade. In addition, Wolak's (2022) approach proposes far fewer products in the forward energy market since our market includes both forward contracts and call options with high time and locational granularity.

Like Wolak (2022), we advocate mandatory forward purchase obligations for LSEs. However, we propose a linear increase in obligations from zero four years ahead to 100 percent one day ahead, rather than Wolak's steep increments (85 percent at four years ahead, 87 percent at three years ahead, 90 percent at two years ahead, and 100 percent at one year ahead). A linear schedule allows LSEs to incorporate new information gradually, improving risk management and reducing price impacts. Moreover, gradual trade creates ample liquidity in each frequent batch auction since each market participant trades a rich set of products in every auction.

3 The forward energy market

3.1 Product definitions

We propose a forward energy market that is centrally operated by the system operator. It is a financial market that trades derivatives of day-ahead energy. Day-ahead energy trades on a nodal level in advanced electricity markets. Our forward energy market aggregates the nodal day-ahead products to load zone levels to limit the number of products while taking the regional characteristics of the electricity system into account.

Types of contract (derivatives of day-ahead prices)	Financial forwards Call options Renewable energy certificates
Time granularity	Monthly products: year–month–hour–we/wd Daily products (only month-ahead): date–hour
Locational granularity	Zonal
Market horizon	4 years ahead until delivery
Auction frequency	Hourly

Table 1: Forward market product definition

The forward energy market allows trading three derivative products in each load zone (see Table 1): First, financial forward energy contracts that should be the primary risk management tool for market participants. Second, European call options with a very high strike price, e.g., 1000 $/MWh. We set such a high strike price because the option's main objective is to manage risks created by large price spikes. The call options are purely financial unlike capacity markets' reliability options, which bundle a physical component (Cramton et al., 2013). Third, Renewable Energy Certificates (RECs) that let market participants manage jurisdictional renewable requirements.

Trading starts four years before the physical delivery of the energy. The three above products are traded for granular delivery periods defined as combinations of year-month-hour-weekend/weekday. For example, Weekdays 8-9 am in May 2018 is a delivery period. The granular delivery periods enable traders to align their derivative purchases with the seasonal and daily cycles of their physical load. We call these granular products "monthly products". Starting four years ahead, agents can trade 2,304 monthly products per zone (48 months, 24 hours per day, and 2 weekend/weekday combinations, which gives 48*24*2=2,304 products).

As an illustration, Figure 1 shows simulated arbitrage-free forward prices for all year-month-hour-weekend product between 2019 and 2022 in the Texas ERCOT market. The graph reveals that the monthly forward prices follow seasonal and daily load cycles, with low prices in shoulder months and at night and high prices during summer and afternoon peak hours.

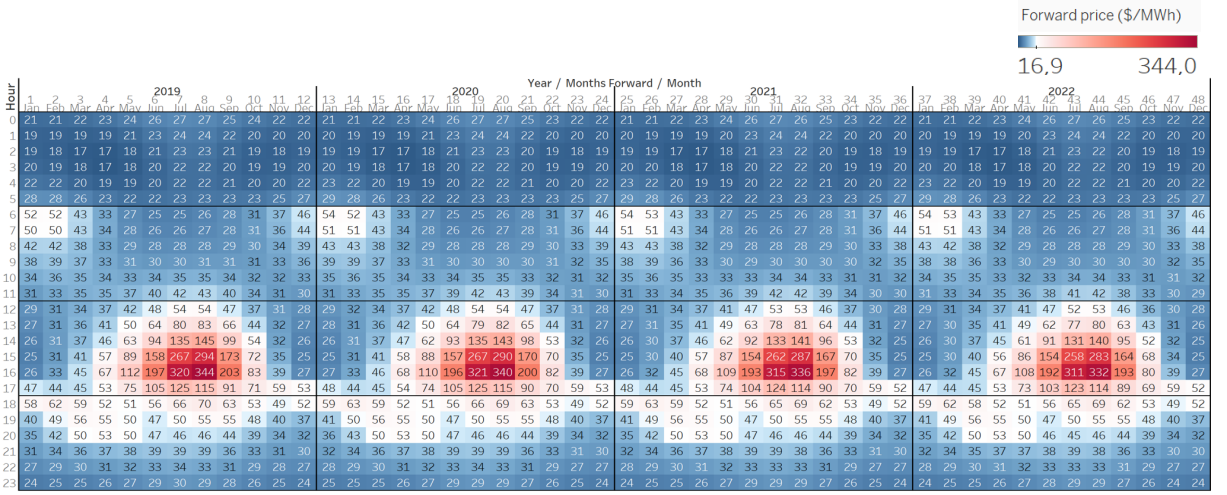


Figure 1: Forward electricity prices for year-month-hour products for weekdays from 2019 to 2022

In addition to the monthly products, there are "daily products" that start trading 30 days before the physical delivery. A daily product is a combination of date and hour of day. For example, 8-9 am on May 15, 2018 would be a daily delivery period. At each point in time, there are 720 (=30*24) daily products for the next 30 days ahead. The daily products should gradually link the coarser monthly products with the underlying day-ahead quantities.

Starting four years ahead of physical delivery, the forward energy market lets agents repeatedly trade every available monthly and daily product in every hour using frequent batch auctions (Budish et al., 2023). The bidding window in each batch auction starts one minute after the hour and lasts until the hour's end. During the bidding window, market participants may adjust their orders. The final orders at the end of the bidding window are binding. Only these binding orders are used in the market clearing optimization.

To increase liquidity and coordinate trade, regulators should implement a modest purchase obligation for LSEs. The obligation starts at 0 percent 48 months ahead and increases linearly to 100 percent of the realized real-time load one day ahead. The LSE can cover its obligation with forward energy or energy options.

The purchase obligation is based on the LSE's real-time load. Recognizing that real-time load is uncertain, the LSE likely wants to buy most of its anticipated load as forward energy and some as energy options to manage risk. For example, the LSE may buy its expected load as forward energy and then sufficient energy options to cover extreme demand scenarios. The LSE is motivated to buy enough energy and options to cover realized load, even in extreme events. The LSE has two incentives to purchase ahead: 1) it must buy any shortfall at the real-time price, and 2) it pays a penalty introduced by the regulator for under-purchases of its real-time load. The system operator can raise the penalty factor if experience shows that LSEs are purchasing too-few options to cover

extreme events. Underestimations of the load that exceed a specified tolerance may also increase collateral requirements.

It may seem extremely complex for market participants to jointly trade thousands of monthly and daily derivative products on an hourly basis. The forward energy market will use the flow trading methodology developed by Budish et al. (2023), which makes trading thousands of products easy for traders and computationally feasible for market operators.

3.2 Flow trading methodology

Flow trading lets market participants place persistent portfolio orders that induce a smooth trade flow among multiple products. Flow trading exploits the power of convex optimization, to simultaneously find market equilibria for a large number of products. The ability to trade thousands of products makes the forward energy market more complete. Moreover, granular products combined with hourly frequent batch auctions allows agents to adjust their portfolio positions efficiently as information changes over time.

We summarize the key features of the flow trading bidding language by presenting two theorems from Budish et al. (2023) and an immediate corollary. The following content until the corollary closely follows Budish et al. (2023).

In each frequent batch auction, flow trading asks traders to submit their orders for a portfolio of products rather than for individual monthly or yearly products. Each order i for the portfolio of products must be expressed as a piece-wise linear net demand curve $D_i(p_i)$:

$$D_i(p_i|\mathbf{w}_i, q_i, p_i^L, p_i^H) := q_i \,\text{trunc}\left(\frac{p_i^H - p_i}{p_i^H - p_i^L}\right) \qquad \text{where } \text{trunc}(z) = \begin{cases} 1, & \text{for } z \geq 1, \\ z, & \text{for } 0 \leq z < 1, \\ 0, & \text{for } z \leq 0. \end{cases} \tag{1}$$

When net demand $D_i(p_i)$ is positive, the trader buys the portfolio while negative net demand indicates that the trader sells it. p_i is the price of the portfolio in order i. $\mathbf{w}_i = (w_{i1}, ..., w_{iN})^T$ is a vector of portfolio weights and w_{in} gives the weight of product n in portfolio order i. A positive weight means that the product is bought while a negative weight means that it is sold (Budish et al., 2023).

Net demand $D_i(p_i)$ is represented as flows over batch intervals, constrained by a cumulative quantity limit $Q_i^{\max} > 0$. The flow rate $q_i > 0$ gives the maximum quantity of portfolio units the agent wants to buy per batch auction until the cumulative limit $Q_i^{\max}$ is reached.

The flow rate allows agents to distribute their trades over time while constantly adjusting the speed at which they trade (Budish et al., 2023).

Moreover, net demand $D_i(p_i)$ is characterized by a lower limit price p_i^L and an upper limit price p_i^H with $p_i^L < p_i^H$. At prices equal to or below p_i^L, the agent wants to buy the portfolio at the maximum flow rate q_i in each batch auction. At prices above p_i^H, the agent has zero demand for the portfolio. Between these bounds $[p_i^L, p_i^H]$, the demand linearly decreases from full quantity at p_i^L to zero at p_i^H. For a sell order, both limit prices are encoded as negative numbers with $p_i^L < p_i^H$ (Budish et al., 2023).

Net demand $D_i(p_i)$ for the portfolio in order i is a function of portfolio price p_i:

$$p_i = \mathbf{w}_i^T \boldsymbol{\pi} = \sum_{n=1}^{N} w_{in} \pi_n. \tag{2}$$

$\boldsymbol{\pi} = (\pi_1, \ldots, \pi_N)^T$ denotes a column vector containing the prices for all individual products $n = 1, ..., N$. The inner product of the product prices and the portfolio weights $\boldsymbol{w}_i$ give the portfolio price.

Let $V_i(x_i)$ be the dollar utility of order i for net demand $x_i = D_i(p_i)$ in portfolio units per hour. To determine $V_i(x_i)$, we express agents' marginal utility function $M_i(x_i)$ as an inverse demand curve $p_i = M_i(x_i)$. The inverse demand curve maps order i's net demand $x_i \in [0, q_i]$ into prices $p_i \in [p_i^L, p_i^H]$ (Budish et al., 2023). Rearranging equation 1 gives

$$M_i(x_i) = p_i^H - \frac{(p_i^H - p_i^L)}{q_i} x_i, \quad x_i \in [0, q_i] \tag{3}$$

$M_i(x_i)$ is the marginal as-bid flow value in dollars per portfolio unit Budish et al. (2023). The utility function $V_i(x_i)$ is defined as the integral over the marginal utility function in the interval $[0, x_i]$:

$$V_i(x_i) = \int_0^{x_i} M_i(u)\, du. \tag{4}$$

$V_i(x_i)$ is quadratic and strictly concave in net demand x_i because marginal utility is linear in x_i (Budish et al., 2023):

$$V_i(x_i) = p_i^H x_i - \frac{(p_i^H - p_i^L)}{2q_i} x_i^2 \tag{5}$$

Budish et al. (2023) assume that $V_i(x_i)$ is defined for all $x_i \in \mathbb{R}$ where the constraint $x_i \in [0, q_i]$ is imposed by the order specification in equation 1.

After all market participants have submitted their orders at the end of the frequent batch auction, the market operator's auction platform processes all orders to find the market equilibrium. The equilibrium prices and quantities should maximize as-bid social welfare. "As-bid" means that the system operator assumes that the net demand curves reflect the

participants' marginal value or marginal cost. Social welfare is maximized when aggregate net demand is zero, and the market clears (Budish et al., 2023).

Budish et al. (2023) formulate the problem of finding market-clearing prices "as two optimization problems: a primal problem of finding quantities that maximize as-bid dollar value and a dual problem of finding prices that minimize the cost of non-clearing prices". The first-order conditions for these two problems allow deriving market-clearing prices and quantities (Budish et al., 2023). The system operator acts analogously to a social planner and chooses a vector of trade rates $\mathbf{x} = (x_1, ..., x_I)$ for all submitted orders i to maximize aggregate utility:

$$\max_{\mathbf{x}} V(\mathbf{x}) = \sum_{i=1}^{I} V_i(x_i), \quad \mathbf{x} \in \mathbb{R}^I, \tag{6}$$

subject to:

$$\sum_{i=0}^{I} x_i \mathbf{w}_i = \mathbf{0} \qquad \text{(market-clearing constraints)} \tag{7}$$

$$x_i \in [0, q_i] \quad \text{for all } i \qquad \text{(trade-rate constraints)} \tag{8}$$

The objective function $V(\mathbf{x})$ is concave since it is a sum of concave functions. The above problem can be written as a quadratic program since the objective function is quadratic and the constraints are linear. Introducing matrix and vector notation, let $\mathbf{W}$ be the $N \times I$ matrix whose ith column is $\mathbf{w}_i$. Let $\mathbf{p}^H$ represent the column vector whose ith element is p_i^H. Let $\mathbf{D}$ denote the $I \times I$ positive definite diagonal matrix whose ith diagonal element is $(p_i^H - p_i^L)/q_i$ (Budish et al., 2023). Then, the problem in equation 6 can be rewritten as:

$$\max_{\mathbf{x}} \left[\mathbf{x}^T \mathbf{p}^H - \frac{1}{2} \mathbf{x}^T \mathbf{D} \mathbf{x} \right] \quad \text{subject to } \mathbf{W}\mathbf{x} = \mathbf{0}, \quad \mathbf{0} \leq \mathbf{x} \leq \mathbf{q} \tag{9}$$

Below, we summarize how Budish et al. (2023) demonstrate that there exist quantities that maximize aggregate utility (Theorem 1) and that there exist market-clearing prices (Theorem 2).

Theorem 1 (Budish et al. (2023))**.** *There exists a unique vector of trade rates* $\mathbf{x}$ *which solves the maximization problem in Equation 9.*

To prove Theorem 1, Budish et al. (2023) use the duality between the problems of finding optimal prices and quantities. They define the following Lagrangian function

$$L(\mathbf{x}, \boldsymbol{\pi}, \boldsymbol{\lambda}, \boldsymbol{\mu}) = \mathbf{x}^T \mathbf{p}^H - \frac{1}{2} \mathbf{x}^T \mathbf{D} \mathbf{x} - \boldsymbol{\pi}^T \mathbf{W} \mathbf{x} + \boldsymbol{\mu}^T \mathbf{x} + \boldsymbol{\lambda}^T (\mathbf{q} - \mathbf{x}) \tag{10}$$

The Lagrangian has three constraints: (1) the market clears ($\mathbf{Wx} = 0$); (2) trade rates are greater than or equal to zero ($\mathbf{x} \geq \mathbf{0}$); (3) the trade rates are less than or equal to their maxima ($\mathbf{x} \geq \mathbf{q}$) (Budish et al., 2023). The dual problem related to the primal problem of maximizing aggregate utility in equation 9 is given as

$$\hat{G}(\boldsymbol{\pi}, \boldsymbol{\lambda}, \boldsymbol{\mu}) = \max_{\boldsymbol{x}} L(\boldsymbol{x}, \boldsymbol{\pi}, \boldsymbol{\lambda}, \boldsymbol{\mu}), \quad \boldsymbol{\pi} \in \mathbb{R}^N, \quad \boldsymbol{\mu} \geq \mathbf{0}, \quad \boldsymbol{\lambda} \geq \mathbf{0} \tag{11}$$

The dual problem is a minimization problem with infimum g given as (Budish et al., 2023):

$$g := \inf_{\boldsymbol{\pi}, \boldsymbol{\lambda}, \boldsymbol{\mu}} \hat{G}(\boldsymbol{\pi}, \boldsymbol{\lambda}, \boldsymbol{\mu}) \qquad \text{subject to } \boldsymbol{\pi} \in \mathbb{R}^N, \quad \boldsymbol{\mu} \geq \mathbf{0}, \quad \boldsymbol{\lambda} \geq \mathbf{0}. \tag{12}$$

The dual problem in equation (10) is formulated as an infimum rather than a minimum because we have not yet shown that there exists a solution (π, λ, μ) that attains the infimum (Budish et al., 2023).

Theorem 2 (Existence of market-clearing (Budish et al., 2023))**.** *There exists at least one optimal solution* $(\boldsymbol{\pi}, \boldsymbol{\lambda}, \boldsymbol{\mu})$ *to the dual problem in equation 12. The solutions* $\mathbf{x}$ *and* $(\boldsymbol{\pi}, \boldsymbol{\lambda}, \boldsymbol{\mu})$ *are a primal-dual pair which satisfies the strict duality relationship* $g = V(x)$*.*

Budish et al. (2023) prove Theorem 2 by using the properties that the primal objective function $V(\mathbf{x})$ is strictly concave and bounded since $V(\mathbf{x})$ is the sum of a finite number of concave quadratic and bounded functions. Moreover all constraints are linear and the no-trade constraint ($\mathbf{x} = \mathbf{0}$) is feasible as it clears the market. With a concave primal problem, a finite supremum on the primal problem, feasibility, and linear constraints, there must then be a dual solution that attains the same value, guaranteeing the existence of market-clearing prices.

Budish et al. (2023) stress that Theorem 2 does not imply that market-clearing prices are unique. Market-clearing prices form a convex set and may be unbounded. For instance, if all orders are buy orders and there are no sell orders, any sufficiently high price clears the market at zero trade. When there is a single buy order and a single sell order for the same product with the same maximum rate, and the buyer's lower price limit exceeds the seller's, an interval of prices allows execution.

Uniqueness of prices is important for the transparency of the market-clearing rules. Therefore, Budish et al. (2023) introduce the following tie-breaking rule that guarantees unique prices: "If more than one price vector supports the optimal quantity vector, select the price vector closest to the prior price vector in Euclidean distance" (Budish et al., 2023).

Corollary 1 (Uniqueness of quantities and prices)**.** *Prices and quantities are unique with the closest-to-prior-prices rule.*

Proof. The set of prices that support the unique optimal quantities is convex. The closest point in a convex set to a given point is unique. □

The closest-to-prior-prices tie-breaking rule guarantees that there is a unique mapping of orders into prices and quantities that maximizes as-bid social welfare. This tie-breaking rule is especially appropriate in our frequent batch auction setting, in which prices evolve slowly from the gradual trade of persistent orders.

Flow trading makes it computationally feasible to find unique prices and quantities quickly even for thousands of products. The flow trading problem is an instance of a "global consensus" problem, which can be efficiently solved via the alternating direction method of multipliers (ADMM) (Boyd et al., 2011). Indeed, we can fully parallelize the solution over each participant's subproblem, enabling any solution speed with additional GPUs. Furthermore, ADMM methods are trivially warm-started, allowing the reuse of the prior solution to achieve rapid convergence.

Budish et al. (2023) demonstrate how computation times vary with the number of orders and products. For instance, with a large number of 100,000 orders and 10,000 products, the computation to find unique prices and quantities takes about 100 seconds when running it on a single server. Hence, clearing the market every hour is feasible even with large numbers of orders and products (Budish et al., 2023).

3.3 Market settlement and collateral requirements

The market operator publishes the unique prices determined by the above flow trading methodology in the first minute of the hour. It also publicly releases the slope of aggregate net demand for each product as an indication of market liquidity. This makes the forward energy market highly transparent.

The auction platform revises each participant's position based on the quantities implied by the prices. Each participant can view and download prices and the revised position anytime during the bidding window. This process repeats every hour. Orders persist until changed or canceled. Thus, if the user wants to maintain the same preferences because nothing has changed, the user does nothing. The same orders will continue to be processed every hour until the user submits a change.

Every hour, the auction platform updates the settlement for each participant. The user is warned if the user's excess collateral falls below a warning trigger. If the user's collateral falls below zero, future trades that would increase the participant's collateral requirement are not allowed. For every order, the portion that would shift the user to a less balanced position is eliminated.

Through knowledge of each agent's position, the system operator can establish highly optimized collateral requirements that maximize market resiliency to systemic events with minimal collateral. The collateral requirements depend on deviations from balanced positions. The exact market rules for collateral requirements will be based on a to-be-developed optimization. This approach will maximize market stability while minimizing unnecessary capital commitments from participants.

The key inputs in determining collateral are 1) the participant's current position, 2) the participant's expected load, and 3) the participant's expected energy production. Each participant reports 2 and 3 to the system operator. Excessive imbalances between estimated and realized load and production increase the participant's collateral requirements, consistent with the higher default risk from larger imbalances. The system operator maintains 1. When the system operator evaluates reported production during net peak load conditions, 3 defines the participant's capacity value, or accredited capacity.

Bilateral forward contracts outside the centralized market are allowed, but must be reported to the system operator to take these contracts into account when adjusting collateral requirements.

Based on the above market rules, we will proceed with a proof-of-concept simulation of our forward energy market for the ERCOT market in Texas. As a first step, the next section introduces a model of ERCOT's day-ahead market. The day-ahead market is fundamental for the forward energy market.

4 Market simulation

In this section, we describe our model of the ERCOT day-ahead market. We jointly model hourly day-ahead electricity prices, hourly net load, hourly solar and wind generation, and daily gas prices for all hours between 2011 and 2022. After simulating joint draws of day-ahead prices, renewable generation, gas prices and net load, we employ a merit order dispatch model to obtain hourly generation quantities and profits for a large sample of power plants.

The regime-switching market model employed here was initially developed by Coulon et al. (2013) and simulated for the ERCOT day-ahead market between 2005 to 2011. In Brandkamp et al. (2025), the model was adapted to account for renewable generation and was calibrated to data from 2011 and 2022. In this paper, we use the model and simulation results created by Brandkamp et al. (2025) and only summarize the main features of their simulation. We refer to Coulon et al. (2013) and Brandkamp et al. (2025) for a detailed exposition of the model.

4.1 Day-ahead market model

Coulon et al. (2013) and Brandkamp et al. (2025) simulate day-ahead prices P_t in hour t using the following exponential function:

$$P_t \;=\; G_t \exp\Big(\alpha_{m_k} \;+\; \beta_{m_k} L_t \;+\; \gamma_{m_k} X_t\Big), \tag{13}$$

G_t is the daily gas price and L_t denotes hourly net load (i.e., load minus wind and solar generation). X_t is a residual process reflecting outages or transmission constraints. Index $m_k \in \{1, 2\}$ indicates that the price is in "normal" regime 1 or in "spike" regime 2. The probability of being in the spike regime increases with net load. Because the exponential function amplifies L_t and X_t differently in each regime, the model captures both typical price variability and rare but severe price spikes. We cap the simulated day-ahead prices at 9,000\$/MWh to account for the price cap in the ERCOT day-ahead market.

We let the logarithm of gas price G_t follow an Ornstein-Uhlenbeck (OU) process:

$$d(\log G_t) \;=\; \kappa_G\Big(m_G - \log G_t\Big)\, dt \;+\; \eta_G\, dW_t^{(G)}. \tag{14}$$

To capture daily and seasonal cycles, we deseasonalize net load $L_t \;=\; S(t) \;+\; \overline{L}_t$ into a seasonal term $S(t)$ and a mean-reverting residual component $\overline{L}_t$ for every hour of day h:

$$S(t) = a_1(h) + a_2(h)\cos(2\pi t + a_3(h)) + a_4(h)\cos(4\pi t + a_5(h)) + a_6(h)t + a_7(h)1_{we} \tag{15}$$

$$d\overline{L}_t = -\,\kappa_L\, \overline{L}_t\, dt \;+\; \eta_L\, dW_t^{(L)} \tag{16}$$

where 1_{we} indicates weekends (Coulon et al., 2013). Similarly, residual process $X_t = S_X(t) + \overline{X}_t$, is deseasonalized:

$$S_X(t) = b_1(h) + b_2(h)\cos(2\pi t + b_3(h)) + b_4(h)\cos(4\pi t + b_5(h)) \tag{17}$$

$$d\overline{X}_t = -\,\kappa_X\, \overline{X}_t\, dt \;+\; \eta_X\, dW_t^{(X)} \tag{18}$$

X_t captures unobserved supply and transmission constraints and random shocks. The deseasonalized processes $\overline{L}_t$ and $\overline{X}_t$ may be correlated, reflecting the fact that extreme demand conditions often coincide with plant and transmission outages due to extreme weather (Coulon et al., 2013).

Indicator m_k defines if day-ahead prices are in normal regime 1 or spike regime 2 (see

Equation 13). m_k is realized by an independent coin flip:

$$m_k = \begin{cases} 1 & \text{with probability } 1 - p_s \Phi\left(\frac{\bar{L}_t - \mu_s}{\sigma_s}\right) \\ 2 & \text{with probability } p_s \Phi\left(\frac{\bar{L}_t - \mu_s}{\sigma_s}\right) \end{cases}$$

$\phi(\cdot)$ represents the normal cumulative distribution function (cdf). The probability of switching to spike regime 2 rises with the deseasonalized net load $\bar{L}_t$, where $\mu_s = 0$ and $\sigma_s = \frac{\eta_L}{\sqrt{2\kappa_L}}$ are the mean and standard deviation of the stationary distribution of $\overline{L}_t$. In both regimes, day-ahead prices follow the same exponential form in Equation 13, but differ in their parameters $\alpha_{m_k}, \beta_{m_k}, \gamma_{m_k}$. In the spike regime, these parameters produce a sharper sensitivity of prices to net load and residual shocks, capturing rare yet extreme price events (Coulon et al. (2013), Brandkamp et al. (2025)).

Brandkamp et al. (2025) calibrate the above regime-switching model to hourly data for ERCOT between 2011 and 2022. Hourly day-ahead electricity prices come from ERCOT (2024c), and hourly system load data from ERCOT (2024b). Daily Henry Hub gas price data is obtained from EIA (2024). In addition, Brandkamp et al. (2025) employ hourly generation profiles of 218 wind farms and 189 solar farms, simulated by ERCOT (2023), and supplement them with aggregate hourly renewable generation data from ERCOT (2024a).

To calibrate the model to the data, Brandkamp et al. (2025) first deseasonalize net load and the residual process X_t. The estimated parameters of the seasonal processes in Equations 15 and 17 are presented in Appendix A in Brandkamp et al. (2025). Next, maximum likelihood is used to estimate the parameters of the OU processes in Equations 14, 16, and 18, and the exponential day-ahead price equation 13. The estimated parameters are summarized in Tables 2 and 3.

κ_L	η_L	κ_G	η_G	m_G	κ_X	η_X	ν
125.571	84,329.524	3.524	0.915	1.159	996.966	40.406	0.092

Table 2: Parameters relating to the stochastic processes for G_t, L_t, and X_t.

α_1	β_1	γ_1	α_2	β_2	γ_2	p_s
1.279	2.39×10^{-5}	0.308	-0.035	7.12×10^{-5}	1.065	0.161

Table 3: Estimated parameters for the day-ahead price function in equation 13

$\beta_2 > \beta_1$ implies that net load and day-ahead prices have a steeper exponential relation in spike regime 2 than in normal regime 1. $\gamma_2 > \gamma_1$ means that random shocks such as

plant or transmission outages also have a stronger effect on day-ahead prices in the spike regime. $p_s = 16.1\%$ indicates that day-ahead prices are in the spike regime in 8.05% ($p_s/2$) of hours (Coulon et al. (2013), Brandkamp et al. (2025)).

In addition to the above regime-switching model, we also utilize the model of hourly solar and wind generation that Brandkamp et al. (2025) estimate for 218 wind farms and 189 solar farms using their generation profiles provided by ERCOT (2023). The model allows simulating hourly solar and wind generation. It captures daily and seasonal generation cycles and accounts for the correlation between each plant's hourly generation and aggregate wind and solar generation (Brandkamp et al., 2025).

4.2 Merit-order model

Based on the above day-ahead market model, Brandkamp et al. (2025) use a merit order model to simulate dispatch and profits for a sample of 655 power plants that operate in the ERCOT market. Table 4 summarizes the number of plants and their capacities by technology. For conventional plants, data on capacity, commissioning dates, heat rates, and variable costs are provided by Mann et al. (2017). For solar and wind farms, data on capacity and commissioning dates is obtained from ERCOT (2023).

Technology	**Plant Count**	**Capacity (MW)**	**% in Total Capacity**
Wind	218	39,203	27.29
Solar	189	24,701	17.19
Gas Combined Cycle	68	35,132	24.45
Gas Steam Turbine	46	11,970	8.33
Gas Open Cycle	83	6,438	4.48
Gas Combustion Engine	10	671	0.47
Lignite	12	7,142	4.97
Coal	20	12,637	8.80
Hydro	5	555	0.39
Nuclear	4	4,981	3.47
Biogas	4	93	0.06
Biomass	2	150	0.10

Table 4: Overview of plant types, their counts, nameplate capacities, and shares in total capacity.

Employing Brandkamp et al.'s (2025) regime switching model and the renewable generation model, we first simulate a large number of day-ahead market states. We define a market state as a set of hourly day-ahead price P_t, net load L_t, gas price G_t, and hourly solar and wind generation values. For each set of values we determine hourly dispatch and profit for each conventional plant using a standard merit order model as presented in Brandkamp et al. (2025). In addition, we use Brandkamp et al.'s (2025) renewable

generation model to simulate corresponding generation and profits for the solar and wind plants.

The large number of simulated market states provides us with a rich distribution of day-ahead prices, quantities, and profits. Using these distributions, we continue deriving optimal trading strategies in our forward energy market.

5 Trading in the forward energy market

5.1 Optimal forwards and option quantities

In this section, we characterize optimal trading strategies for market participants following Brandkamp et al. (2025). We start by modeling day-ahead market profits for a load-serving entity (LSE) and a generator (GEN) in hour t as:

$$\pi_{DA_t}^{LSE} = (R_Y - P_t)q_t \qquad \pi_{DA_t}^{GEN} = P_t q_t - c_t(q_t)$$

where P_t is the day-ahead price, q_t is the agent's load or generation, R_Y the fixed retail rate, and $c_t(q_t)$ the generator's cost function. For some generation technologies, costs may vary with fuel prices on a yearly or daily basis (Brandkamp et al., 2025).

Both agents can hedge their day-ahead market risk by buying or selling forwards and European call options. The total hedged profit for agent $i \in \{\text{LSE, GEN}\}$ in hour t is:

$$\pi_t^i \;=\; \pi_{DA_t}^i - \left(F_M^p - P_t\right) h_M - \left(V_M - v_t\right) z_M,$$

h_M and z_M are the quantities of forwards and call option contracts for delivery period M. F_M^p is the forward price in delivery period M, V_M is the option price and $v_t = \max\{P_t - K_M, 0\}$ is the option payoff with strike price K_M (Brandkamp et al., 2025).

Forwards and option quantities h_M or z_M can be positive or negative. Negative quantities indicate that the agent sells while positive quantities indicate that it buys. Importantly, we assume that the chosen forwards and option quantities do not affect agents' bidding incentives, and equilibrium prices and quantities in the day-ahead market (Brandkamp et al., 2025).

Agents select the optimal forwards and option quantities h_M and z_M under uncertainty about day-ahead prices P_t, load q_t, and generation costs $c_t(\cdot)$. We define option and forward quantities as optimal if they maximize agent i's expected utility from profits in

delivery period M:

$$\max_{h_M, z_M} E\Big[U\Big(\pi^i_{t\in M}\Big)\Big] \tag{19}$$

The optimal quantities $h^*_M(F^p_M, V_M)$ and $z^*_M(F^p_M, V_M)$ that solve the above problem are functions of the prices for forwards and options F^p_M and V_M. Unlike Brandkamp et al. (2025), we let agents express preferences for forwards and options quantities for prices that may deviate from arbitrage-free levels. To integrate this with the flow trading methodology (Section 3.2), agents specify their net demand for a combined portfolio of forwards and options as a downward sloping piece-wise linear function of the portfolio price (i.e., a linear combination of forwards and option prices).

To simulate optimal net demand curves, we assume that agents have constant absolute risk aversion (CARA) utility functions. With CARA utility, we require numerical optimization to find optimal forwards and option quantities because day-ahead market profits are not normally distributed due to price-spikes and correlation between prices and load (Lapan et al. (1991), Brandkamp et al. (2025)).

5.2 Trade-to-target strategies

At any given time, the net demand curve specifies the optimal forward and option quantities based on current information about the distribution of day-ahead prices and load. However, executing the entire net demand in a single order would adversely affect market prices. Instead, large agents typically split their orders into smaller chunks and trade gradually to mitigate price impact (Budish et al., 2023). Trading gradually also has the advantage that agents can constantly adjust their orders in response to new information. Incremental trading, thereby, facilitates risk managements.

Flow trading makes gradual trade over time much easier than conventional limit order bids. Flow trading asks agents to express a trade rate which determines how fast agents want to trade to satisfy their net demand. This makes it easy to split the large total net demand into small fractions that are traded over time (Budish et al., 2023). Agents can adjust trade rate and net demand curves every hour to respond to new information.

A straightforward strategy within this framework is "trade-to-target". Agents set their net demand as a target to be reached by the start of physical delivery. They also specify the trade rate at which they want to move toward the target. For example, an LSE may set its net demand target for forwards equal to its expected load it needs to serve during the delivery period. The LSE could select the trade rate such that the fraction of net demand it purchases increases linearly from zero to its target as time moves from 48 months ahead to day-ahead. Its call option target may be enough to cover potential

demand surges during extreme weather.

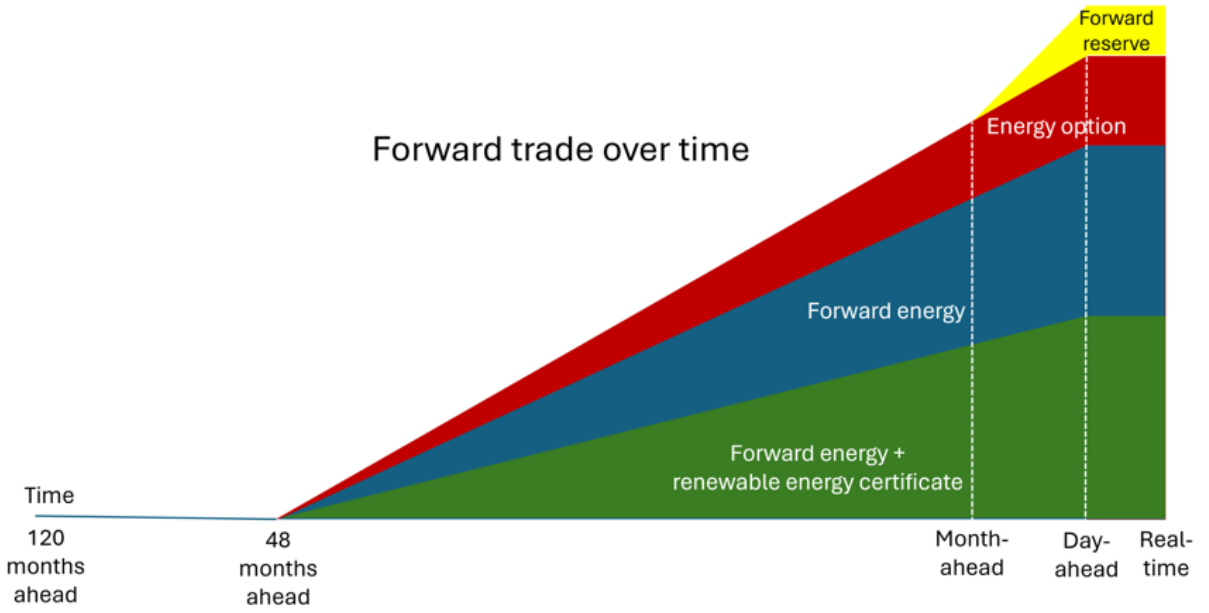


Figure 2: Illustration of a trade-to-target strategy for an LSE (not to scale)

Figure 2 illustrates a trade-to target strategy for an LSE that has a 50 percent renewable energy requirement. The LSE purchases 50 percent of its expected demand with renewable energy certificates (RECs, green) and the remaining forward energy without RECs (blue). To cover unanticipated demand, it buys energy options (red). Beginning one month ahead, the LSE may purchase forward reserves (yellow) to get some additional forward energy if required by expected market conditions. Target purchases are completed one day ahead. Agents then respond to new information with intraday adjustments until real-time.

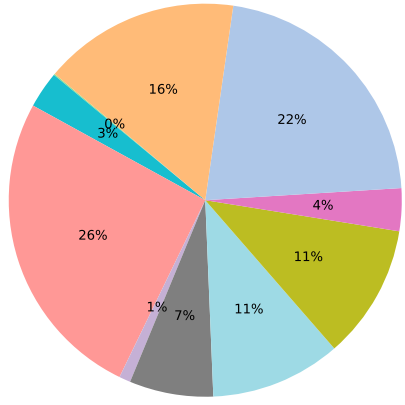
Flow trading also makes it easy for the LSE to substitute forwards and options if their relative prices change since net demand is always expressed for a portfolio of forwards and options.

In the next section, we simulate linear trade-to-target strategies in the forward energy market for representative LSEs and generators with diverse risk preferences, load-serving obligations, and power plant portfolios. We derive forward market clearing prices and quantities using Budish et al.'s (2023) flow trading methodology. We use these clearing prices and quantities to calculate hourly profits for each market participant. Finally, we compare the effectiveness of the trade-to-target strategy to alternative benchmark strategies. For instance, a simple benchmark strategy is that agents hedge their expected annual base load or base generation using yearly futures contracts. Seasonal and monthly expected peak load or generation could be hedged with more granular quarterly and monthly products. An alternative benchmark strategy is that agents do not hedge on the forward market but trade only on the day-ahead market.

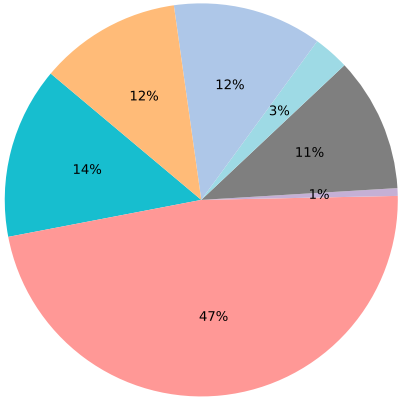
6 Simulation results

In this section, we numerically simulate hedging strategies for a set of representative generators and LSE for all hours in 2019. We initialize the simulation on $t =$ December 1, 2018 and run hourly frequent batch auction in each hour until December 31, 2019. At the start of the simulation, we initialize all random processes at their long-term average, i.e. $\overline{L}_t = \overline{X}_t = 0$, $log(G_t) = m_G$ (Coulon et al., 2013). Moreover, we set the risk-free interest rate at 2% and choose a high call option strike price of \$1,000/MWh so that the option covers only the tail of the day-ahead price distribution.

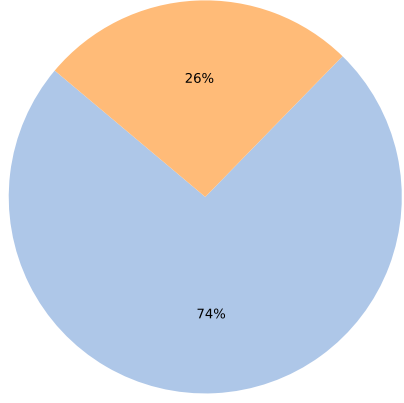
(a) Legend



(b) Owner 1 (34.0 GW and 147 plants)



(c) Owner 5 (8.0 GW and 29 plants)



(d) Owner 8 (3.0 GW and 16 plants)

Figure 3: Capacity mix per owner in % of total capacity (total capacity in brackets)

We create a set of representative generation companies and load-serving entities (LSEs) to analyze a realistic market structure. For the generation side, we create 10 generation companies by allocating the 655 power plants in our sample to one of these companies such that the resulting power plant portfolios mimic representative generation firms (Mann et al., 2017). As an example, the capacity mix of three generation companies is shown in

Figure 3. The capacity mixes for all other generation companies are given in Figures 14 and 15 in Appendix D.

Generation owner 1 in Figure 3b represents a large incumbent generation firm with 147 power plants and 34 GW installed capacity. Its plant portfolio is technologically well diversified and representative for the Texan market. Owner 5 in Graph 3c is a smaller mostly conventional generation company with 8 GW installed capacity and 29 plants. More than two-thirds of its portfolio consists of gas plants. Owner 8 in Figure 3d mimics a small renewable-only player who has 3 GW installed capacity across 16 solar and wind farms. Due to their different size and technology mix, these generation companies might have very different hedging needs.

On the demand side, we also create 20 representative LSEs. We assume that each LSE serves on average a certain share of aggregate load. Demand market shares range from 2% to 12% of aggregate load. Following Brandkamp et al. (2025), each LSE's load follows aggregate load while a random noise process causes the LSE's load to occasionally deviate from aggregate load. We assume perfect competition on the demand side, i.e., all LSEs charge their end-customers the same retail price equal the average annual day-ahead price plus a 10% margin that allows LSEs to cover their fixed costs and to make a profit (Peura and Bunn (2021), Brandkamp et al. (2025)).

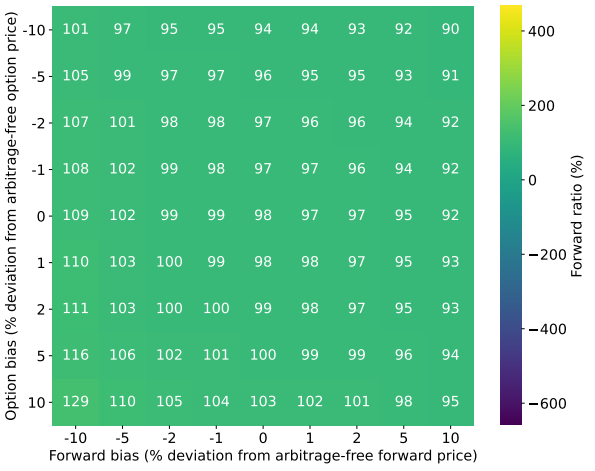
6.1 Net demand curves

In this section, we present simulated net demand curves to examine agents' preferences for forwards and options. We focus on simulating hedging strategies for incumbent generation owner 1 (see Figure 3b) and for a medium-size LSE with 5% market share.

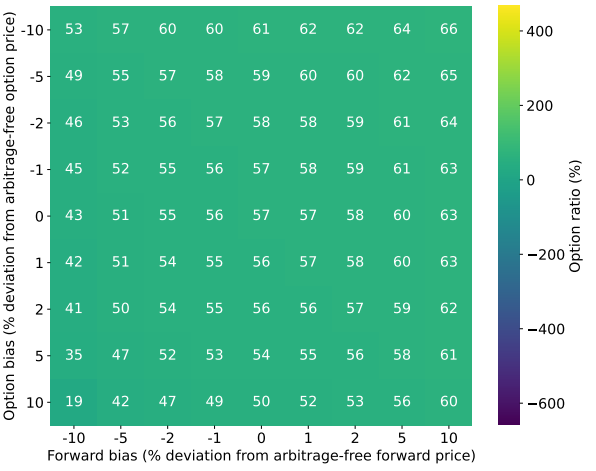
Figure 4, shows matrices of optimal forward and call option ratios for the monthly delivery period on Weekdays 4-5 pm in August 2019. These ratios are expressed as a fraction of the agents' expected load in the delivery period. A 2% option bias indicates that the option price is 2% above its arbitrage-free level. For these matrices, we parameterize agents' risk preferences using a moderate relative risk coefficient of 0.2[2]. The delivery period Weekdays 4-5 pm in August 2019 is a peak period with large and frequent price spikes (Brandkamp et al., 2025)

[2]Following the literature, we transform the relative risk coefficient as an input for CARA utility functions in order to make risk preferences comparable between players who have very different profit scales. To do so, we choose a relative risk coefficient as an exogeneous parameter. Then, we divide the relative risk coefficient by the agent's average profit in the delivery period to translate the relative risk coefficient into an absolute risk coefficient. Locally at the average profit level, the relative risk coefficient and the absolute risk coefficient describe the same risk aversion level. We assume this absolute risk coefficient to be constant across all profit levels to use it as an input for the CARA utility function (Raskin and Cochran (1986), Newbery (1989), Lapan and Moschini (1994), Brandkamp et al. (2025)).

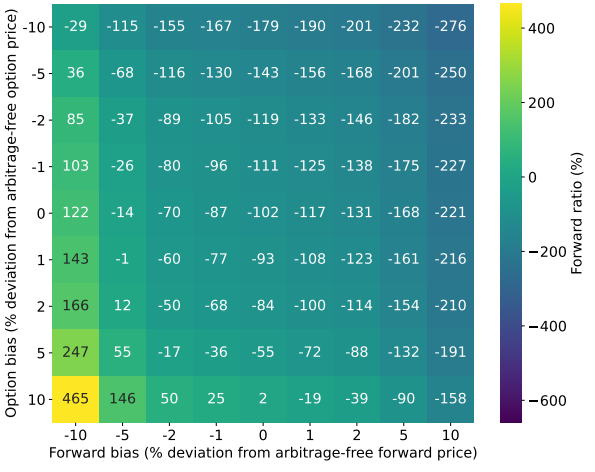
Graph 4b reveals that the moderately risk-averse LSE wants to buy 98% of its expected load in forwards and 57% in options when both forwards and options have zero bias (i.e., prices are at their arbitrage free levels). The generator wants to sell 102% of expected load in forwards and only 2% in options for unbiased prices. With a negative forward bias, the generator reduces its short forward position and the LSE increases its long forward position (Graphs 4a and 4c). To offset the large forward position, the LSE cuts its long option position while the generator takes large short option positions (Graphs 4b and 4d). Conversely, a positive forward bias makes buying forwards less attractive such that the LSE reduces its long forward position and the generator goes short in forwards. At the same time, a high forward price prompts both players to buy more options (or at least sell less of them). Similarly, a negative option price bias makes buying options more attractive relative to buying forwards, and vice versa.



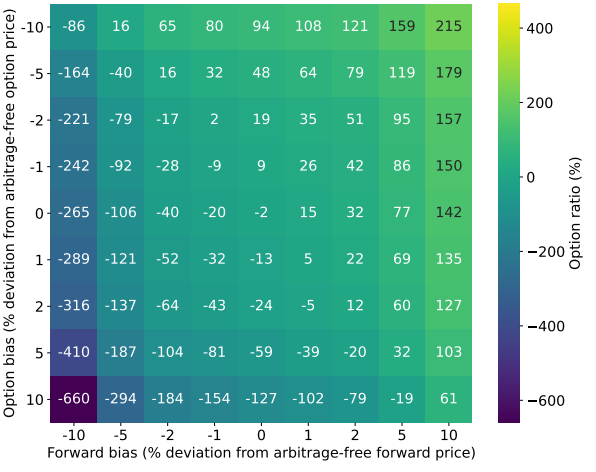
(a) LSE's forward ratios



(b) LSE's option ratios



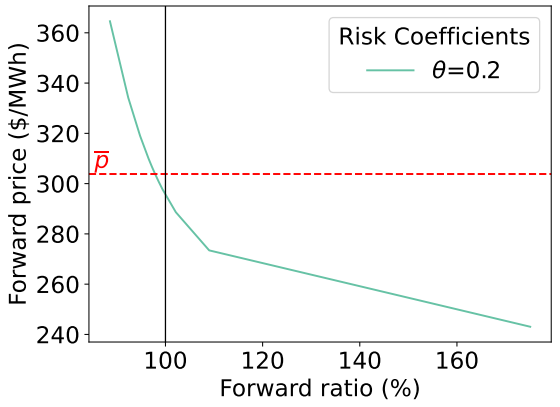
(c) Generator's forward ratios



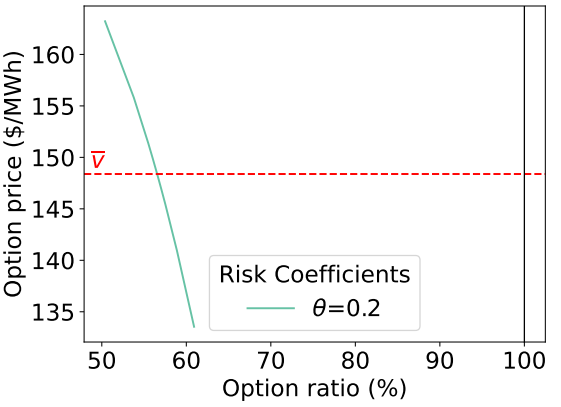
(d) Generator's option ratios

Figure 4: LSE and generator's optimal forward and option ratios as a function of the bias in forward and option prices for peak delivery period weekdays 4-5 pm in August 2019 for a relative risk coefficient of 0.2

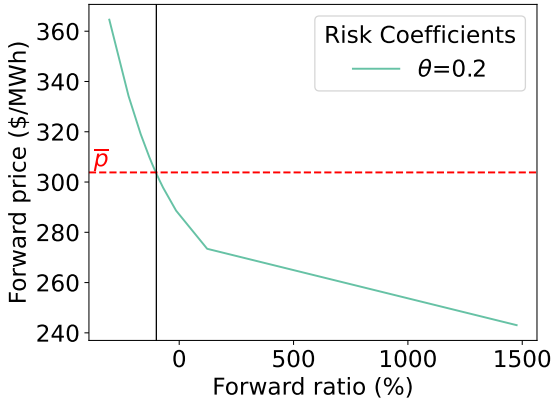
For both agents, forward and option ratios are more elastic to forward prices than to option prices. Figures 5a and 5c show the agents' downward-sloping inverse demand curves for forwards when fixing the option price at its arbitrage-free level (zero bias). Plots 5b and 5d depict the inverse demand curves for options when holding the forward price unbiased. The plots highlight that the own-price elasticity of the option demand is smaller than for the forward demand. Especially the LSE's option demand is hardly elastic to the option price. In addition, Figure 7 in Appendix A indicate that the cross-price elasticity of the option demand with respect to the forward price exceeds its own-price elasticity. Option demand rises in the forward price. Demand for forwards is moderately elastic to option prices. However, the forward's own-price elasticity is larger than its cross-price elasticity with respect to the option price, especially for the generator.



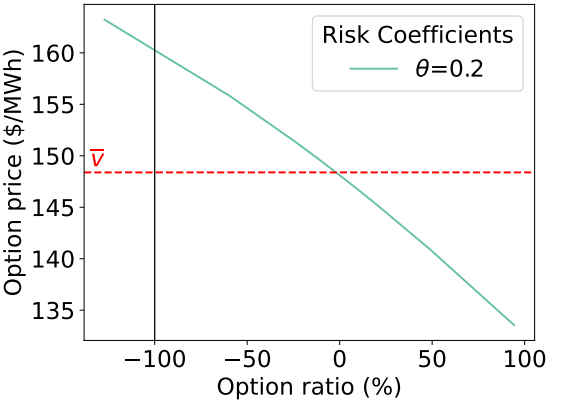
(a) LSE's forward ratios



(b) LSE's option ratios



(c) Generator's forward ratios



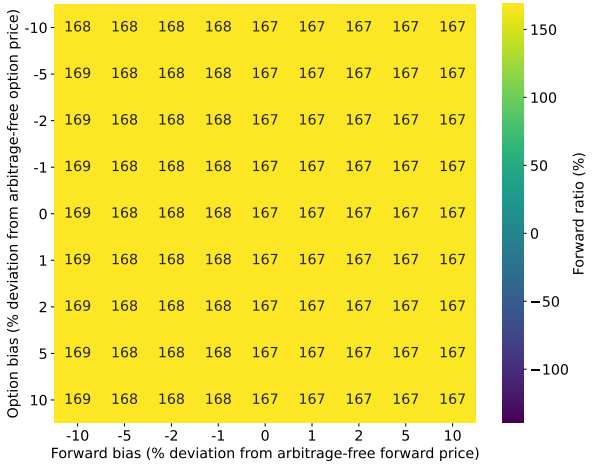
(d) Generator's option ratios

Figure 5: LSE and generator's net demand curves for forwards and options for peak period weekdays 4-5 pm in August 2019 by risk aversion

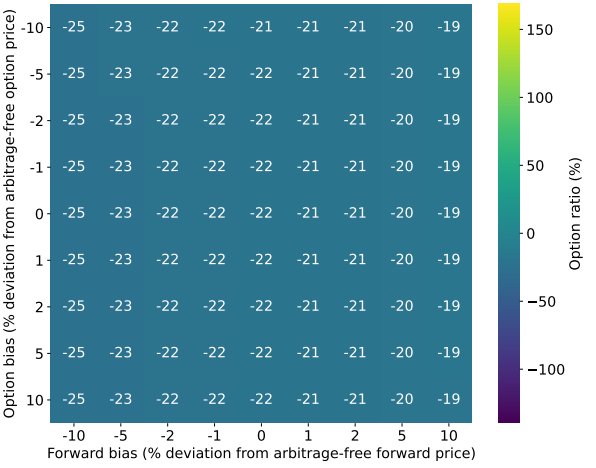
The forward-price elasticity of forwards and options is larger for substantial negative biases than for positive ones. This asymmetry arises because a positive forward bias induces a

short forward position, which can incur extreme losses during peak periods with high price spikes (Brandkamp et al., 2025). Consequently, both the generator and the LSE react more strongly to negative biases.

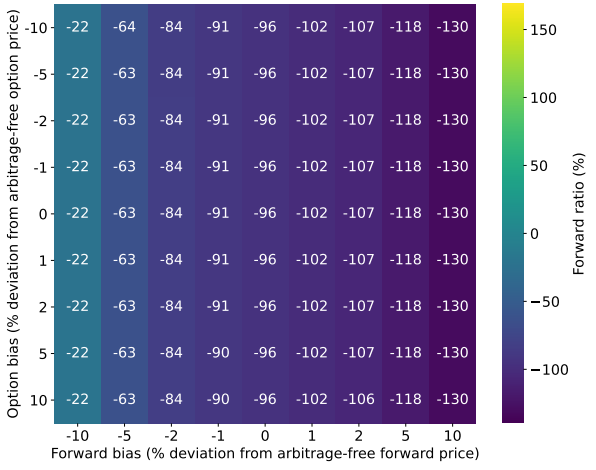
Overall, the generator takes larger arbitrage positions in response to biased prices, likely because the LSE faces more extreme tail risks in the day-ahead market (Brandkamp et al., 2025). Therefore, the LSE is more cautious to speculate. Notably, the generator takes substantial arbitrage positions for relatively small price biases of -10% to 10% for this peak period, where large and frequent price spikes make speculation highly profitable.



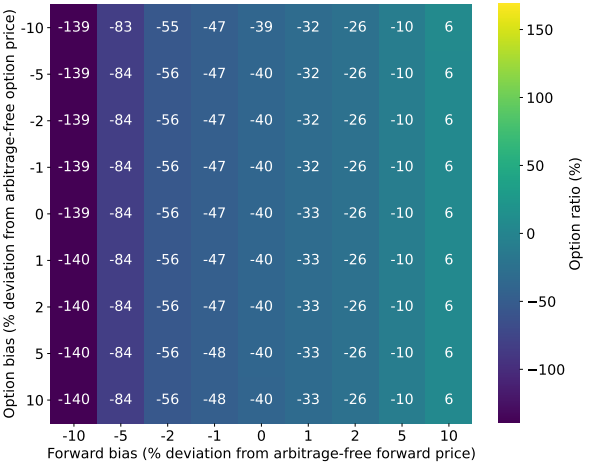
(a) LSE's forward ratios



(b) LSE's option ratios



(c) Generator's forward ratios



(d) Generator's option ratios

Figure 6: LSE and generator's optimal forward and option ratios as a function of the bias in forward and option prices for off-peak delivery period weekends 4-5 am in May 2019 for a relative risk coefficient of 0.2

In contrast, Figure 6 presents similar matrices for the off-peak period Weekends 4-5 am in May 2019, when price spikes are small and rare. Here, both agents take much smaller arbitrage positions. Arbitrage is less attractive in off-peak periods with smaller price

spikes. Moreover, in the off-peak period, net demand is almost insensitive to changes in the option price. The option has a very small value relative to the forward because simulated day-ahead prices hardly ever exceed the strike price of $\$1,000$/MWh in this off-peak period. Nonetheless, both agents still opt for substantial short option positions. The LSE finds it optimal to short options to offset its large long forward position.

Remarkably, even with a 10% positive forward bias, the generator only wants to sell at most 130% of expected demand forward while the LSE wants to buy at least 167% forward. If only these two agents participated in the in the market, an even larger forward bias would be required to clear the market.

However, risk preferences play a key role for agents' appetite to arbitrage. Appendix B compares the ratio matrices for nearly risk-neutral agents (relative risk coefficient 0.001) with those for highly risk-averse agent (risk coefficient 1), both for the off-peak and peak period.

Both agents take very large arbitrage positions when they are nearly risk-neutral. Interestingly, the almost-risk neutral LSE wants to speculate more with options in the off-peak period than in the peak period as a comparison of Figures Figures 8a, 8b, 10a, and 10b in Appendix B highlight. By contrast, the moderately risk-averse LSE (risk coefficient 0.2) wants to arbitrage more in the peak period than in the off-peak period, as shown above.

The arbitrage positions for the nearly risk-neutral agents are likely unrealistically large. Even risk-neutral agents likely take smaller arbitrage positions due to collateral requirements. So far, we have not modeled these requirements. In the future, we will extend the objective function in equation 19 in section 5.1 such that it contains a penalizing collateral component that increases when agents take speculative imbalanced positions to limit arbitrage.

The Figures in Appendix B also reveal that the agents speculate much less when they are highly risk-averse (risk coefficient 1). Especially in the off-peak period, highly-risk averse agents barely arbitrage. It would likely require very large positive biases in options and forward prices to clear the market if all market participants were highly risk-averse. However, it seems unlikely that the majority of generation companies and LSEs are highly risk-averse.

A distinctive feature of our market design is the high strike price of $\$1,000$/MWh for the call option. Appendix C explores the impact of a lower strike price of \$200/MWh on net demand. For arbitrage-free prices, Brandkamp et al. (2025) finds that a lower strike price induces agents to choose more options and less forwards because the option grants better protection from moderate price spikes if the strike price is lower. In Appendix C, we reproduce this finding. In addition, we show that a low strike price of \$200/MWh incentivizes larger arbitrage positions compared to the higher $\$1,000$/MWh strike price.

7 Discussion

In the above simulations, we have shown that the forward energy market enables generators and LSEs to effectively manage risk. Combinations of forward contracts and call options allow agents to reduce profit volatility and to handle tail risks.

The essential innovation of our proposal is that forwards and options are traded gradually. We have demonstrated that gradual trade leads to smooth and slow movements of prices and quantities. Our approach achieves smooth price movements because it incentivizes market participants to provide a constant flow of liquidity for thousands of granular products. Price signals for forward energy, thereby, become more stable and reliable.

Stable and transparent price signals provide market participants with crucial information for efficient operation and investment. Granular forward prices enable demand and supply resources to create maximum value in their operation throughout the day, season, and year. This value motivates efficient investment, the main driver of competition. The prices also stimulate innovation in new resource types, especially resources that create value from flexibly responding to prices. Batteries and other low-carbon technologies are good examples. Demand-side innovation benefits from transparent prices. LSEs and other service providers can offer valuable services that optimize the use of low-carbon technologies to maximize consumer welfare. Energy efficiency programs also benefit from the multi-year forward price information.

In addition, the forward energy market would improve resiliency and reliability. Robust forward prices would amplify incentives to invest in technologies encouraging price-responsive demand, such as electric vehicles and smart homes. Retail providers would be encouraged to offer dynamic rate plans that allow consumers to create value by being flexible. These dynamic rates could include automatic hedging via forward purchases such that the dynamic rate reduces downside consumer risk relative to a fixed rate (Brandkamp, 2025). Reliable price information four years ahead would give households, service providers, and industry the information necessary to make these investment decisions.

Long-term price signals also support generation companies to manage the substantial risks involved in investing in new generation assets. Thereby, the forward energy market might replace capacity markets and strategic reserves, or at least reduce their relevance. Capacity markets are adopted to strengthen investment incentives. Flaws in the day-ahead and real-time markets may depress spot revenues below desired investment levels. The flaws are 1) a too-low price cap, 2) treatment of nonconvex costs, and 3) unpriced operator decisions, such as intraday commitments for reliability. These flaws create a "missing money" problem (Joskow (2008), Cramton et al. (2013)). Capacity markets address the missing money problem by creating additional revenue streams for generators.

The major problem of capacity markets is market power. Capacity markets use big-event auctions to procure capacity. Typically, a single auction procures 100 percent of the required capacity three years ahead. Since some market participants are dominant, the scope for exercising market power is considerable. Modern capacity markets rely on procedures to mitigate market power such as price caps or minimum offer prices. However, these procedures are controversial and imperfect (Patterson and Reiter (2016), Macey and Ward (2021)).

By contrast, our forward energy market leaves little room for exercising market power since it encourages granular and gradual trade over many years. Participants trade forward small quantities from near-balanced positions (anticipated load + sales $\approx$ anticipated production + purchases). Therefore, they have little incentive or opportunity to exercise market power.

At the same time, the forward energy market effectively addresses the three above flaws that capacity markets are supposed to tackle: With a robust forward energy market, the regulator can raise the price cap because market participants are in a nearly balanced position and sufficiently hedged from high real-time prices. Nonconvex costs become less important with robust forward prices that introduce a significant volume of convex arbitrage bids. If the forward energy market was combined with intraday rolling settlement, the intraday reliability decisions are optimized and efficiently priced. By contrast, existing capacity markets do not directly address these underlying spot market problems.

Ditching capacity markets will not compromise reliability and resiliency. LSEs have a strong incentive to buy forward, especially with options, because the joint occurrence of day-ahead price spikes and high retail demand exposes LSEs to enormous downside risk. In addition, the regulator should introduce a penalty that LSEs pay for any quantity not purchased in advance. The penalty provides an extra incentive to purchase energy options for load that is not expected but may develop in real-time. Real-time purchases and imbalance penalties are paid from collateral. The collateral requirement increases with the size of the imbalance, consistent with the higher default risk from larger imbalances. Generation companies' incentives to sell options stems from LSEs' willingness to pay a small risk premium to be protected from adverse downside risks. The risk premium provides an additional revenue stream that helps generators to cover their investment costs.

These incentives to buy options should be strong enough for the generators and LSEs to take action to cover their load even in extreme weather events. Resiliency depends on these incentives. The regulator should raise the day-ahead price cap or the penalty factor if the incentives prove too weak. These parameters need to be set to achieve reliability and resiliency goals. The penalty factor is easy to raise if experience demonstrates that LSEs buy insufficient load forward to cover extreme events.

Overall the forward energy market is effective in guaranteeing the reliability and resiliency of the electricity system and in offering attractive risk management tools. Yet, one might wonder if it is necessary that the system operator establishes such a new centrally-organized market. Private exchanges like ICE and CME already organize established markets for forward energy contracts and options.

However, these private markets have severe problems. Liquidity in private exchanges is poor for products more than one year ahead. There are significant frictions due to the duopoly providers' profit incentives, which include charging high fees for services, such as low-latency data feeds and co-location services, that are only needed because of a flawed trading format. The trading format provides too little time and location product granularity, and participants need expensive algorithmic tools to slice orders into thousands of pieces to limit adverse price impact. Because of these misaligned incentives of the private exchanges, the forward energy market can and should be managed by the independent system operator, which alone is motivated to adopt an efficient and transparent firm energy market.

Through knowledge of positions, the system operator can establish highly optimized collateral requirements that maximize market resiliency to systemic events with minimal collateral. The collateral requirement would depend on deviations from balanced positions. Markets fail when counterparties become unreliable. Optimized collateral is critical to minimizing this vulnerability at the least cost.

8 Conclusion

Electricity markets worldwide need to foster rapid innovation to accommodate the energy transition. Innovation is best accomplished with a market design grounded on first principles. The foundation is the spot market, which optimizes the operation of existing resources to satisfy electricity needs at the least cost. Complementing an efficient spot market, we propose a novel forward market design that allows trading of granular forward contracts and European call options, enabling hedge positions closely aligned with actual load profiles. Our design leverages Budish et al.'s (2023) flow trading technology to ensure liquidity and mitigate price impact through gradual, small-quantity trades in hourly batch auctions.

In this project, we develop a full-scale, proof-of-concept simulation of our forward energy market design within Texas's ERCOT market spanning twelve years. This simulation aims to demonstrate the feasibility of our novel market design. Using a regime-switching model, we simulate the distribution of day-ahead profits for representative generators and LSEs. Based on these day-ahead profit distributions, we derive net demand curves for

forwards and options for CARA utility-maximizing agents.

Our simulations indicate that risk preferences critically shape agents' net demand curves. With high risk aversion, both generators and LSEs tend toward nearly vertical net demand curves because agents are unwilling to take on arbitrage risk. Such high risk aversion would force market clearing prices for forwards and options to be substantially above arbitrage-free levels. Generators display a greater willingness to arbitrage as the face lower downside risks in the day-ahead market than LSEs. As risk aversion diminishes, net demand curves become less vertical, especially for generators. Flatter demand curves will likely lead market-clearing prices to converge closer (within 10%) to arbitrage-free benchmarks. However, nearly risk-neutral behavior produces unrealistically large arbitrage positions, underscoring the need to incorporate collateral requirements in our simulations in the future.

We also observe that net demand for both forwards and options is more responsive to changes in forward prices than in option prices. Moreover, net demand demand reacts more acutely to negative forward price biases than to positive ones. A positive bias in the forward price incentivizes large short positions, which can trigger large downside risks.

In peak periods marked by large price spikes, arbitrage positions are considerably larger than in off-peak periods. Net demand for forwards and options becomes almost inelastic to the option price in off-peak periods because the option has a very small value in off-peak periods with rare and small price spikes.

Lastly, lowering the option strike price from \$1,000/MWh to \$200/MWh shifts agents' behavior by increasing option positions and reducing forward positions, as the lower strike offers better protection against moderate price spikes. Moreover, agents tend to engage more in arbitrage with a lower strike price.

In our future work, the simulated net demand curves above will feed as trading strategies into the flow trading methodology to yield market clearing prices and quantities in each hourly batch auction. We will investigate how clearing prices and quantities evolve as they get closer to their physical delivery periods. We will examine to what extend equilibrium prices deviate from arbitrage-free levels. Moreover, how agents' expected profits, volatility, and downside tail risk are affected by trading in a liquid forward energy market.

To implement our market design in practice, we suggest an incremental approach: Initially, the market operator should introduce an hourly, 30-day ahead forward energy (and reserve) market while retaining existing capacity requirements. The incremental implementation would operate as described above but with a weakening of the mandatory purchase obligation. The obligation starts at 0 percent of the anticipated load 30 days ahead to avoid a discontinuous purchase obligation. LSE obligations could increase linearly from 0 to 100 percent from 30 to 1 day ahead.

The incremental approach allows stakeholders to experience the benefits of liquid forward trading and improved price signals without overhauling current capacity mechanisms. Incremental adoption can occur at a modest cost and with little delay because the changes do not alter the core systems. Subsequent extension to a longer forward window is easy. Forward trading is particularly valuable within the 30 day window before physical delivery due to higher volumes and volatility.

Following this incremental approach, regulators could pilot our forward energy market without interfering with existing market design. When the advantages of our design for price discovery and risk management become apparent, regulators can easily extend the market by including more products and extend the trading period to four years ahead or even longer.

References

Allaz, B., & Vila, J.-L. (1993). Cournot competition, forward markets and efficiency. *Journal of Economic Theory*, *59*(1), 1–16. https://doi.org/10.1006/jeth.1993.1001

Australian Competition and Consumer Commission. (2023). Competition in retail electricity market not delivering for all customers. https://www.accc.gov.au/media-release/competition-in-retail-electricity-market-not-delivering-for-all-customers

Black, F. (1971). Toward a fully automated stock exchange, part i. *Financial Analysts Journal*, *27*(4), 28–35. https://doi.org/10.2469/faj.v27.n4.28

Borenstein, S. (2002). The trouble with electricity markets: Understanding california's restructuring disaster. *Journal of Economic Perspectives*, *16*(1), 191–211. https://doi.org/10.1257/0895330027175

Borenstein, S. (2007). Customer risk from real-time retail electricity pricing: Bill volatility and hedgability. *The Energy Journal*, *28*(2), 111–130. http://www.jstor.org/stable/41323097

Boroumand, R. H., Goutte, S., Porcher, S., & Porcher, T. (2015). Hedging strategies in energy markets: The case of electricity retailers. *Energy Economics*, *51*, 503–509. https://doi.org/10.1016/j.eneco.2015.06.021

Brandkamp, S. (2025). Hedging households against extreme electricity prices. *University of Cologne, Working Paper Series in Economics*, (106). https://ideas.repec.org/p/kls/series/0106.html

Brandkamp, S., Cramton, P., Dark, J., Hoy, D., & Malec, D. (2025). Hedging electricity price spikes with forwards and options. *University of Maryland Working Paper*. https://cramton.umd.edu/papers2020-2024/brandkamp-et-al-hedging-with-forwards-and-options.pdf

Brown, D. P., & Sappington, D. E. M. (2023). Load-following forward contracts. *The Energy Journal*, *44*(3), 187–222. https://doi.org/10.5547/01956574.44.2.DBRO

Budish, E., Cramton, P., Kyle, A. S., Lee, J., & Malec, D. (2023). Flow trading. *National Bureau of Economic Research, Working Paper*, (31098). https://doi.org/10.3386/w31098

Budish, E., Cramton, P., & Shim, J. (2015). The high-frequency trading arms race: Frequent batch auctions as a market design response. *The Quarterly Journal of Economics*, *130*(4), 1547–1621. https://doi.org/10.1093/qje/qjv027

Coulon, M., Powell, W. B., & Sircar, R. (2013). A model for hedging load and price risk in the texas electricity market. *Energy Economics*, *40*, 976–988. https://doi.org/10.1016/j.eneco.2013.05.020

Cramton, P. (2017). Electricity market design. *Oxford Review of Economic Policy*, *33*(4), 589–612.

Cramton, P. (2022). Fostering resiliency with good market design: Lessons from texas. *ECONtribute Discussion Paper*, (145). https://www.econstor.eu/handle/10419/252306

Cramton, P., Brandkamp, S., Dark, J., Hoy, D., Malec, D., Ockenfels, A., & Wilkens, C. (2024). A forward energy market to improve resiliency. *University of Maryland Working Paper*. https://cramton.umd.edu/papers2020-2024/cramton-et-al-forward-energy-market.pdf

Cramton, P., Ockenfels, A., & Stoft, S. (2013). Capacity market fundamentals. *Economics of Energy & Environmental Policy*, *2*(2), 27–46. https://doi.org/10.5547/2160-5890.2.2.2

de Frutos, M.-Á., & Fabra, N. (2012). How to allocate forward contracts: The case of electricity markets. *European Economic Review*, *56*(3), 451–469. https://doi.org/10.1016/j.euroecorev.2011.11.005

Energy Information Administration. (2024). Henry hub natural gas spot price. https://www.eia.gov/dnav/ng/hist/rngwhhdD.htm

ERCOT. (2023). Ercot wind profiles and solar pv profiles, 1980-2022.

ERCOT. (2024a). Historical dam load zone and hub prices. https://www.ercot.com/mp/data-products/data-product-details?id=np4-180-er

ERCOT. (2024b). Hourly load data archives. https://www.ercot.com/gridinfo/load/load_hist

ERCOT. (2024c). Interval generation by fuel reports (2011-22). https://www.ercot.com/gridinfo/generation

Fabra, N. (2023). Reforming european electricity markets: Lessons from the energy crisis. *Energy Economics*, *126*, 106963. https://doi.org/10.1016/j.eneco.2023.106963

Genoese, F., Drabik, E., & Egenhofer, C. (2016). The eu power sector needs long-term price signals. *CEPS Special Report*, (135). https://ssrn.com/abstract=2782355

Graf, C., Kuppelwieser, T., & Wozabal, D. (2024). Frequent auctions for intraday electricity markets. *The Energy Journal*, *45*(1), 231–256.

Joskow, P. L. (2008). Capacity payments in imperfect electricity markets: Need and design. *Utilities Policy*, *16*(3), 159–170. https://doi.org/10.1016/j.jup.2007.10.003

Keppler, J. H., Quemin, S., & Sagan, M. (2023). Why the sustainable provision of low-carbon electricity needs hybrid markets: The conceptual basics. https://hal.science/hal-04231032/

Kyle, A. S. (1985). Continuous auctions and insider trading. *Econometrica*, *53*(6), 1315–1335. https://doi.org/10.2307/1913210

Kyle, A. S., & Lee, J. (2017). Toward a fully continuous exchange. *Oxford Review of Economic Policy*, *33*(4), 650–675. https://doi.org/10.1093/oxrep/grx042

Lapan, H., & Moschini, G. (1994). Futures hedging under price, basis, and production risk. *American Journal of Agricultural Economics*, *76*(3), 465–477. https://doi.org/10.2307/1243658

Lapan, H., Moschini, G., & Hanson, S. D. (1991). Production, hedging, and speculative decisions with options and futures markets. *American Journal of Agricultural Economics*, *73*(1), 66–74. https://doi.org/10.2307/1242884

Macey, J. C., & Ward, R. (2021). Mopr madness. *Energy Law Journal*, *42*(1), 67–122. https://heinonline.org/HOL/Page?handle=hein.journals/energy42&div=10&g_sent=1&casa_token=&collection=journals

Mann, N., Tsai, C.-H., Gülen, G., Schneider, E., Cuevas, P., Dyer, J., Butler, J., Zhang, T., Baldick, R., & Deetjen, T. (2017). Capacity expansion and dispatch modeling: Model documentation and results for ercot scenarios. *The Full Cost of Electricity. The University of Texas at Austin Energy Institute*. https://energy.utexas.edu/sites/default/files/UTAustin_FCe_ERCOT_2017.pdf

Newbery, D. (1989). The theory of food price stabilisation. *The Economic Journal*, *99*(398), 1065–1082. https://doi.org/10.2307/2234088

Newbery, D. (2016). Missing money and missing markets: Reliability, capacity auctions and interconnectors. *Energy Policy*, *94*, 401–410. https://doi.org/10.1016/j.enpol.2015.10.028

Patterson, D., & Reiter, H. (2016). Chasing the uncatchable: Why trying to fix mandatory capacity markets is like trying to win a game of whack-a-mole. *Public Utilities Fortnightly*, *June*. https://www.proquest.com/docview/1812902078?sourcetype=Trade%20Journals

Peura, H., & Bunn, D. W. (2021). Renewable power and electricity prices: The impact of forward markets. *Management Science*, *67*(8), 4772–4788. https://doi.org/10.1287/mnsc.2020.3710

Raskin, R., & Cochran, M. J. (1986). Interpretations and transformations of scale for the pratt-arrow absolute risk aversion coefficient: Implications for generalized stochastic dominance. *Western Journal of Agricultural Economics*, 204–210. https://www.jstor.org/stable/40987816

Redl, C., Haas, R., Huber, C., & Böhm, B. (2009). Price formation in electricity forward markets and the relevance of systematic forecast errors. *Energy Economics*, *31*(3), 356–364. https://doi.org/10.1016/j.eneco.2008.12.001

Schlecht, I., Maurer, C., & Hirth, L. (2023). Financial contracts for differences. *ZBW-Leibniz Information Centre for Economics*.

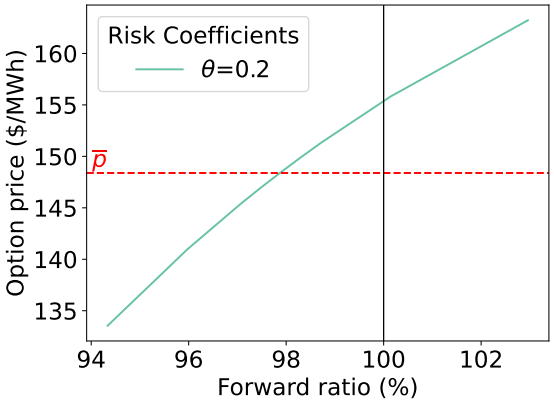
Vayanos, D. (1999). Strategic trading and welfare in a dynamic market. *The Review of Economic Studies*, *66*(2), 219–254. https://doi.org/10.1111/1467-937X.00086

Wolak, F. A. (2022). Long-term resource adequacy in wholesale electricity markets with significant intermittent renewables. *Environmental and Energy Policy and the Economy*, *3*(1), 155–220. https://doi.org/10.1086/717221

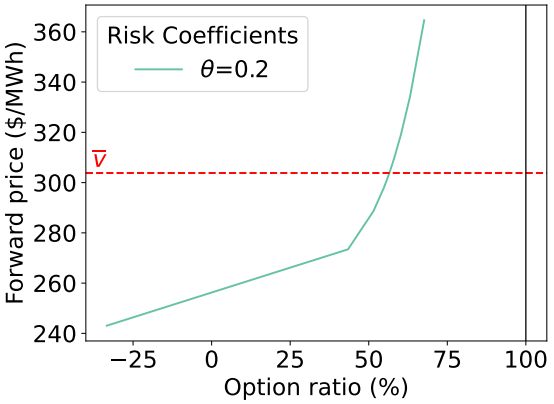
Appendices

A Net demand curves for forwards and options

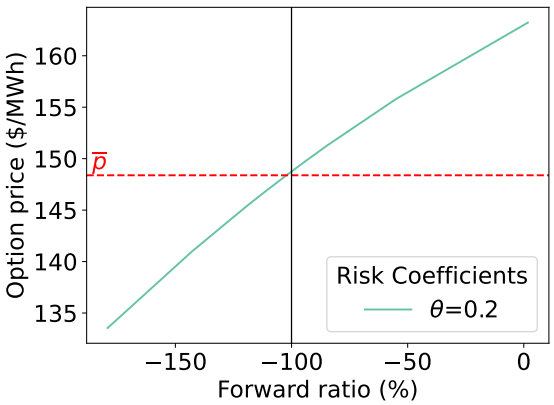
In this appendix, we investigate how the net demand for forwards reacts to the option price and how the net demand for options reacts to the forward price. Figures 7a (LSE) and 7c (generator) indicate that net demand for forwards increases in the option price when fixing the forward price at arbitrage-free levels. Similarly, demand for options also increases in the forward price when setting the option price to its unbiased values as Figures 7b (LSE) and 7d (generator) highlight. For both agents, option demand is highly sensitive to the forward price. By contrast, forwards demand is less sensitive to changes in the option price.



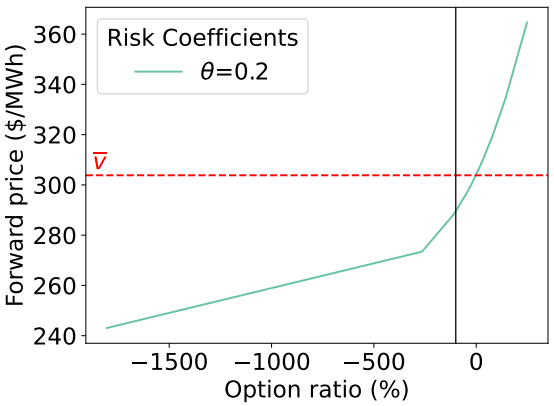
(a) LSE's forward ratios



(b) LSE's option ratios



(c) Generator's forward ratios

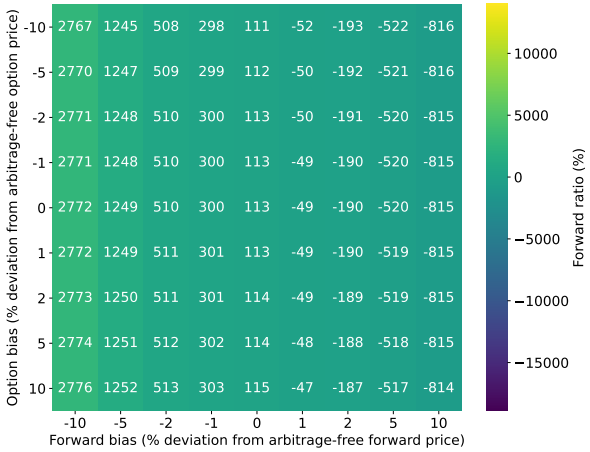


(d) Generator's option ratios

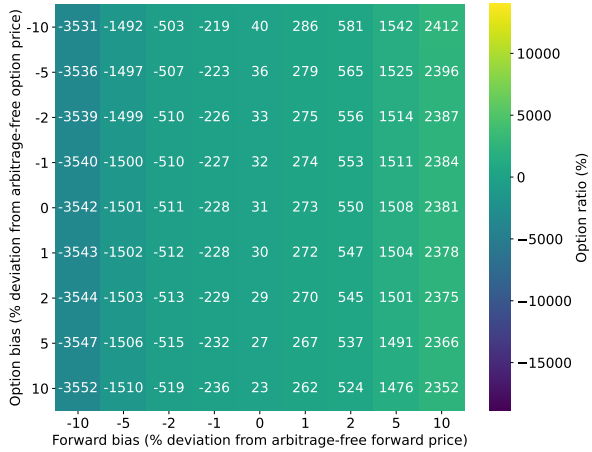
Figure 7: LSE and generator's inverse net demand curves for forwards as a function the option price and for options as a function of the forward price for peak period weekdays 4-5 pm in August 2019 by risk aversion

B Net demand heat maps by risk preferences

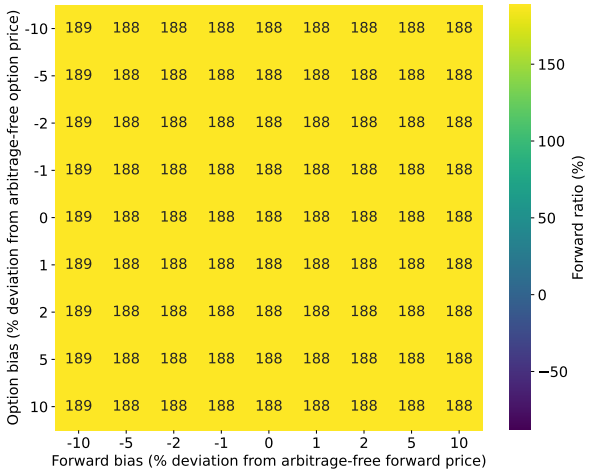
In this appendix, we show additional heat maps for forward and option ratios as a function of forward and option prices to study how agents' risk preferences affect their net demand for forwards and options. The first two figures show the demand matrices for the off-peak period weekends 4-5 am in May 2019 for the LSE (Figure 8) and the generator (Figure 9), respectively. Figures 10 (LSE) and 11 (generator) present the same matrices for the peak period August 4-5 pm in August 2019.



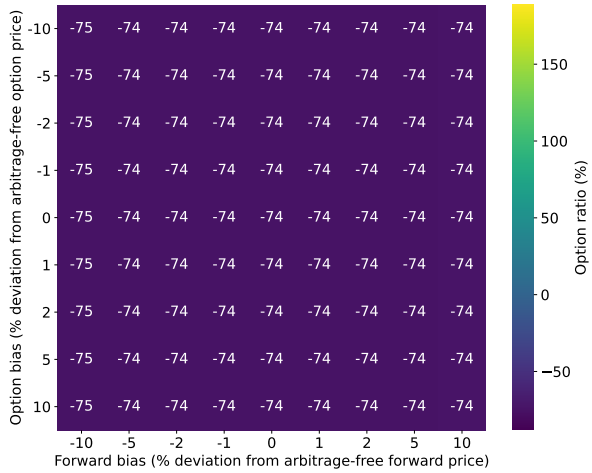
(a) Almost risk-neutral LSE's forward ratios



(b) Almost risk-neutral LSE's option ratios



(c) Highly risk-averse LSE's forward ratios

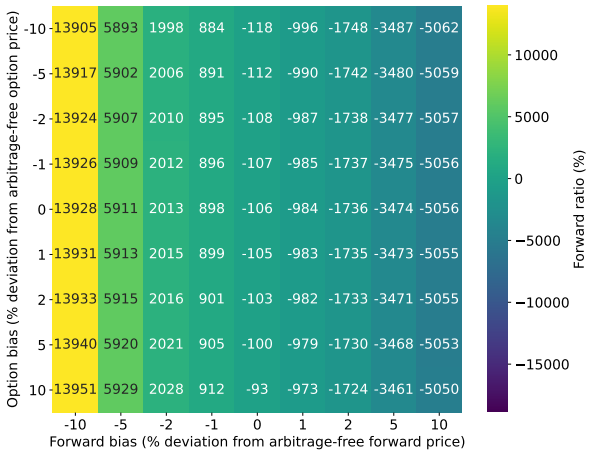


(d) Highly risk-averse LSE's option ratios

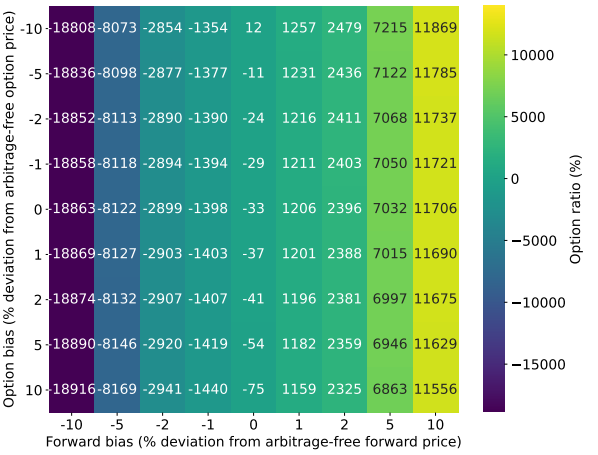
Figure 8: LSE's optimal forward and option ratios as a function of the bias in forward and option prices for off-peak delivery period weekends 4-5 am in May 2019 for near risk neutrality (risk coefficient of 0.001) and high risk aversion (risk coefficient 1)

Figures 8 (LSE) and 9 (generator) show the heat maps for almost risk-neutral agents (with relative risk coefficient of 0.001) and highly risk averse agents (risk coefficient 1). The nearly risk-neutral agents take very large speculative arbitrage positions compared

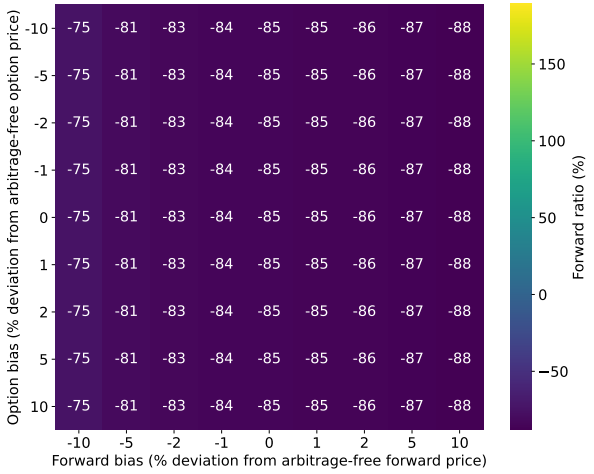
to the moderate risk-aversion level of 0.2 analyzed in Figure 4 in 5.1. The highly risk-averse generator takes much smaller arbitrage positions than the moderately risk averse generator while the highly risk-averse LSE hardly arbitrages.



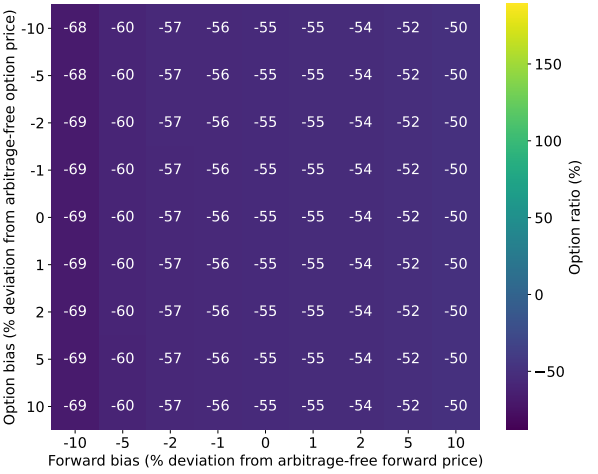
(a) Almost risk-neutral generator's forward ratios



(b) Almost risk-neutral generator's option ratios



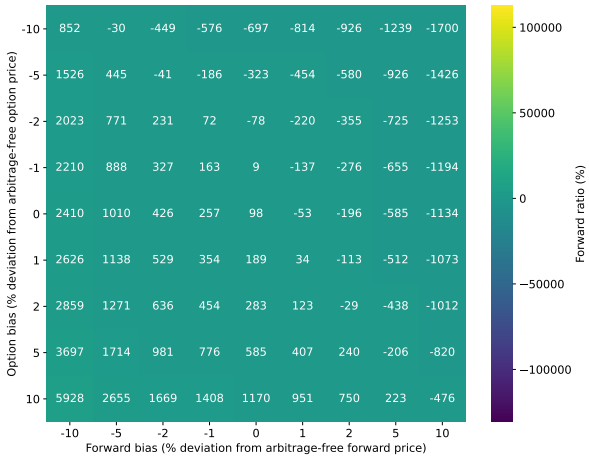
(c) Highly risk-averse generator's forward ratios



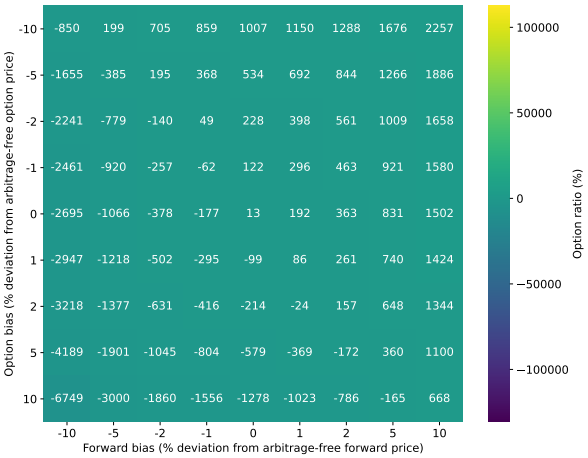
(d) Highly risk-averse generator's option ratios

Figure 9: Generator's optimal forward and option ratios as a function of the bias in forward and option prices for off-peak delivery period weekends 4-5 am in May 2019 for near risk neutrality (risk coefficient of 0.001) and high risk aversion (risk coefficient 1)

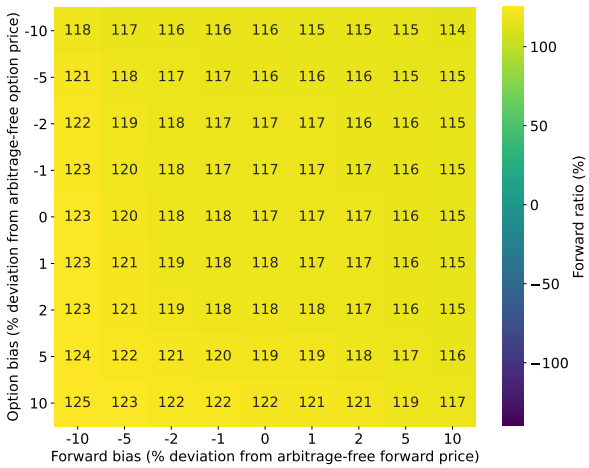
Figures 10 (LSE) and 11 (generator) show the analogous heat maps for the peak period. In the peak period, the almost risk-neutral agents also heavily arbitrage, while the risk-averse agents take smaller arbitrage positions.



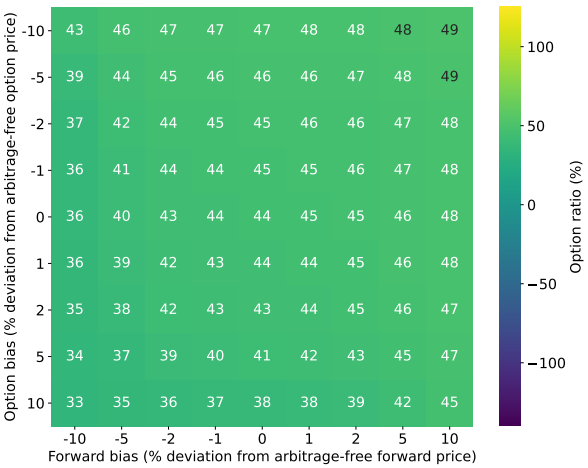
(a) Almost risk-neutral LSE's forward ratios



(b) Almost risk-neutral LSE's option ratios

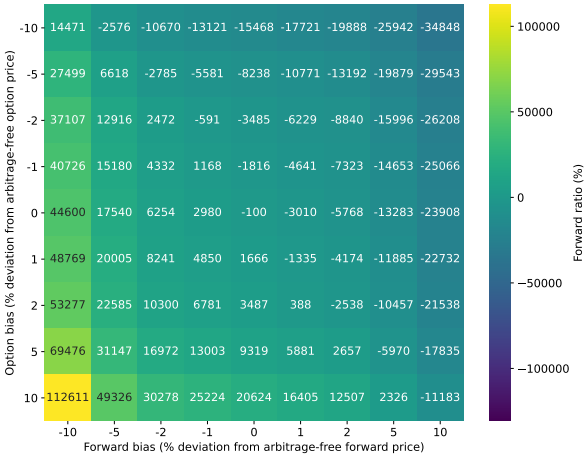


(c) Highly risk-averse LSE's forward ratios

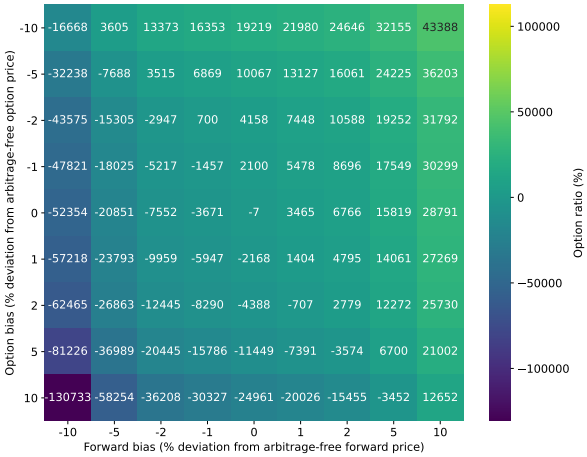


(d) Highly risk-averse LSE's option ratios

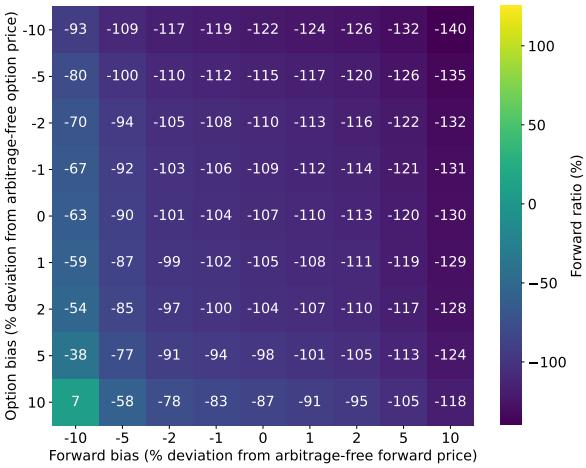
Figure 10: LSE's optimal forward and option ratios as a function of the bias in forward and option prices for peak delivery period weekdays 4-5 pm in August 2019 for near risk-neutrality (risk coefficient of 0.001) and high risk aversion (risk coefficient 1)



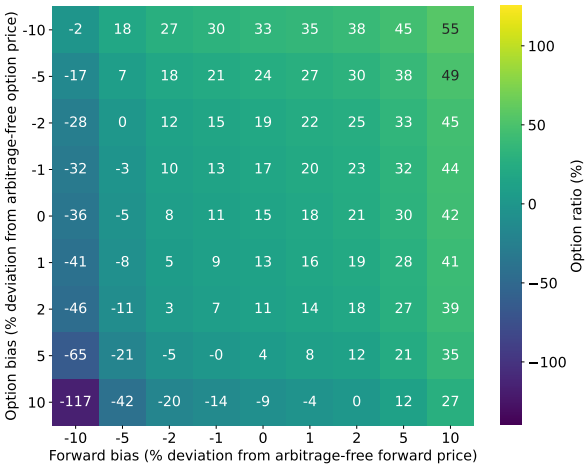
(a) Almost risk-neutral generator's forward ratios



(b) Almost risk-neutral generator's option ratios



(c) Highly risk-averse generator's forward ratios

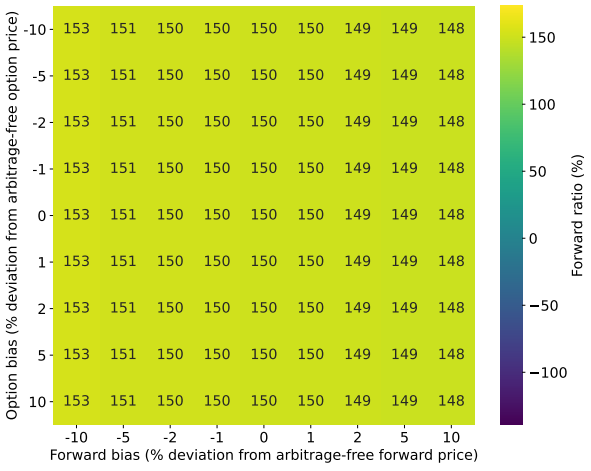


(d) Highly risk-averse generator's option ratios

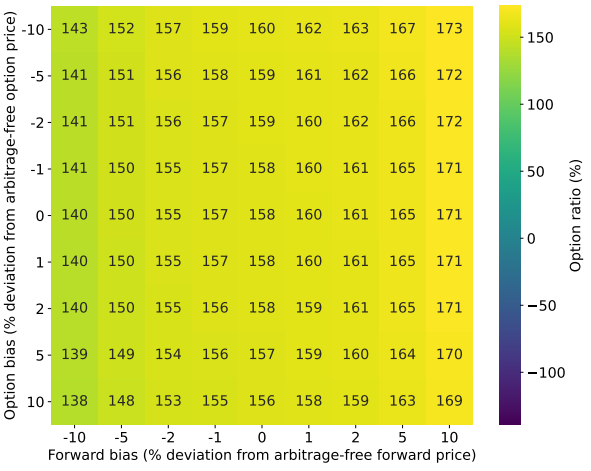
Figure 11: Generator's optimal forward and option ratios as a function of the bias in forward and option prices for peak delivery period weekdays 4-5 pm in August 2019 for near risk-neutrality (risk coefficient of 0.001) and high risk aversion (risk coefficient 1)

C Net demand heat maps for a low strike price

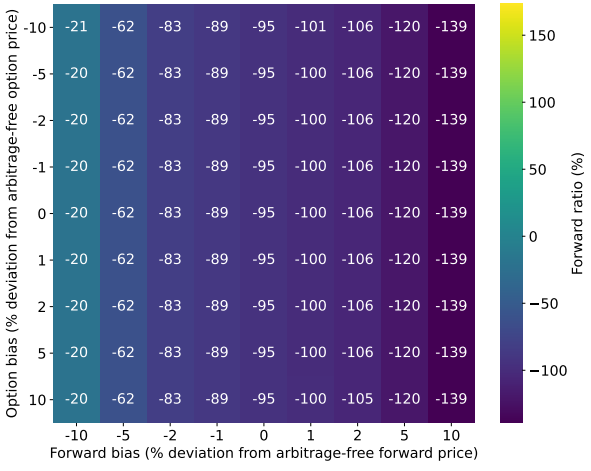
In this appendix, the below figures examine the impact of selecting a lower strike price of \$200/MWh on agents' net demand. Figure 12 depicts the off-peak results and Figure 13 the peak results. With the low strike price, agents choose larger option positions and smaller forward positions compared to the high strike price of \$1,000/MWh as shown in Graph 4 in Section 6.1. Brandkamp et al. (2025) has already established this finding for arbitrage-free prices. Additionally, the below figures demonstrate that a lower strike price of \$200/MWh encourages agents to take larger arbitrage positions compared to a higher strike price of \$1,000/MWh.



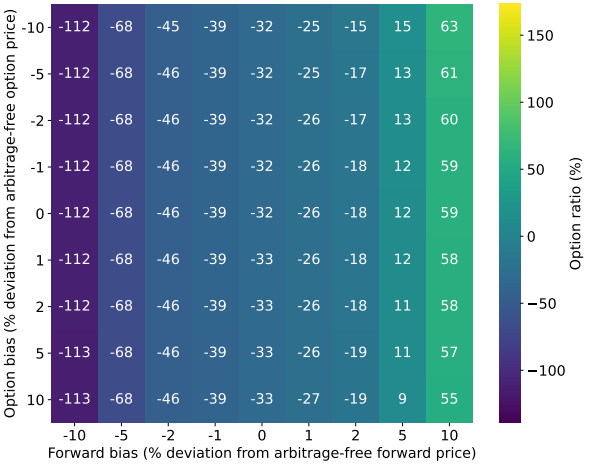
(a) LSE's forward ratios



(b) LSE's option ratios

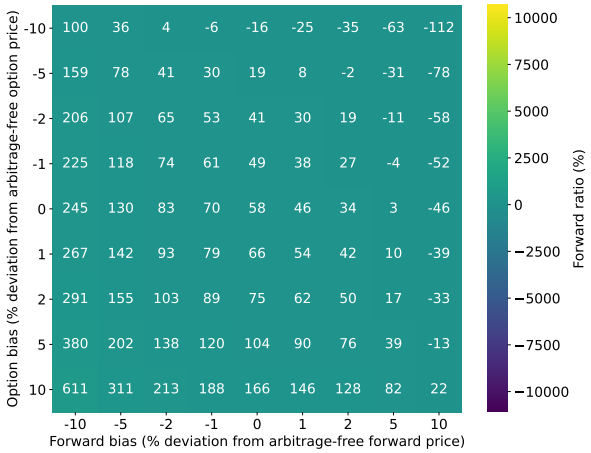


(c) Generator's forward ratios

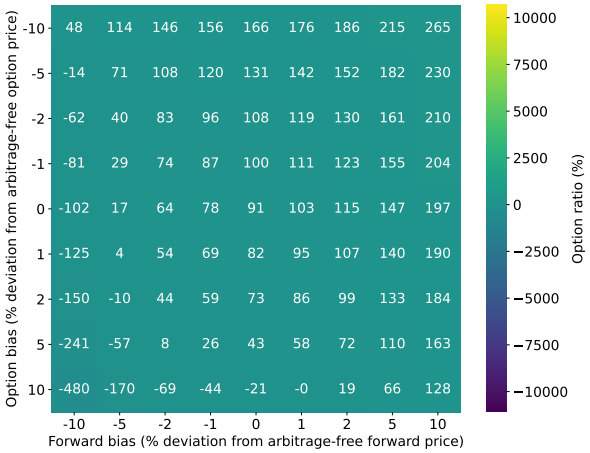


(d) Generator's option ratios

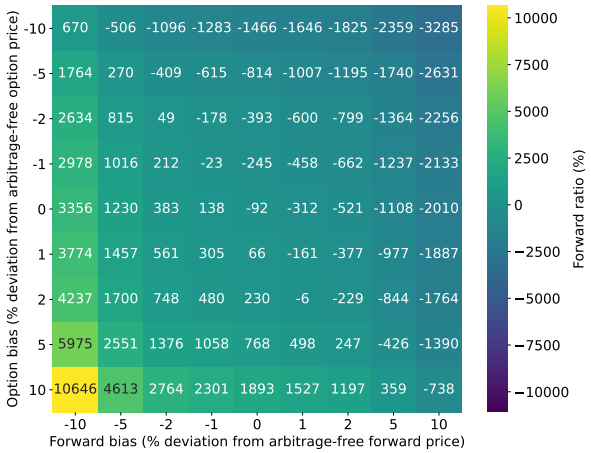
Figure 12: LSE and generator's optimal forward and option ratios as a function of the bias in forward and option prices for off-peak period weekends 4-5 am in May 2019 for a relative risk coefficient of 0.2 and a low strike price of \$200/MWh



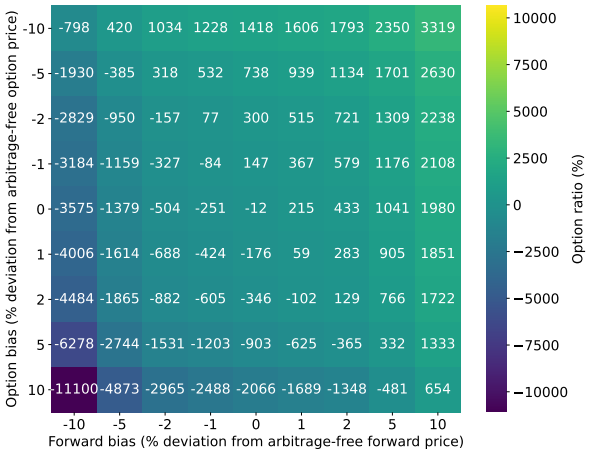
(a) LSE's forward ratios



(b) LSE's option ratios



(c) Generator's forward ratios

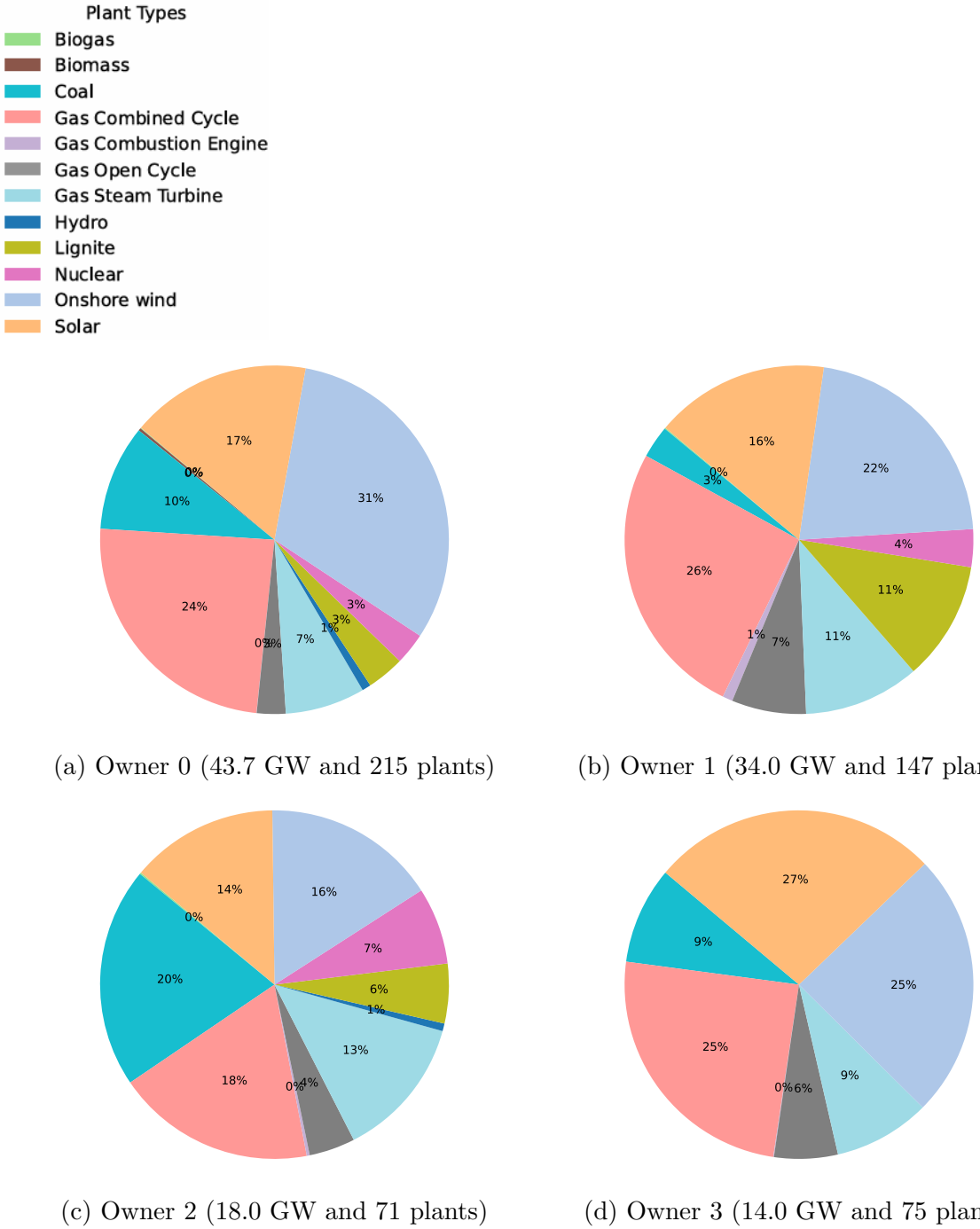


(d) Generator's option ratios

Figure 13: LSE and generator's optimal forward and option ratios as a function of the bias in forward and option prices for peak period weekdays 4-5 pm in August 2019 for a relative risk coefficient of 0.2 and a low strike price of $200/MWh

D Capacity mixes of the representative generators

The below figures show the capacity mixes of the simulated representative generation companies we created based on the power plant datasets by Mann et al. (2017) and ERCOT (2023). For each generation company, its total installed capacity and its number of power plants are given in brackets.



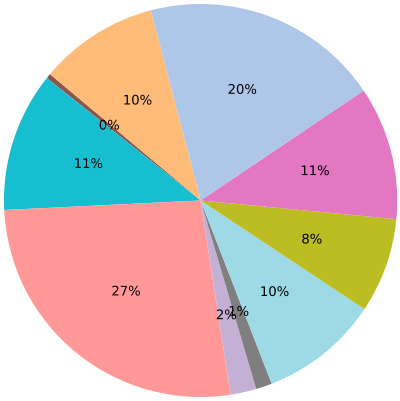
(a) Owner 0 (43.7 GW and 215 plants)

(b) Owner 1 (34.0 GW and 147 plants)

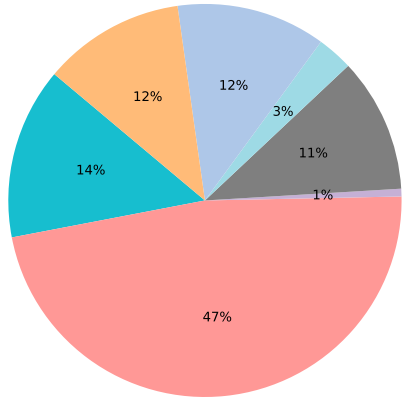
(c) Owner 2 (18.0 GW and 71 plants)

(d) Owner 3 (14.0 GW and 75 plants)

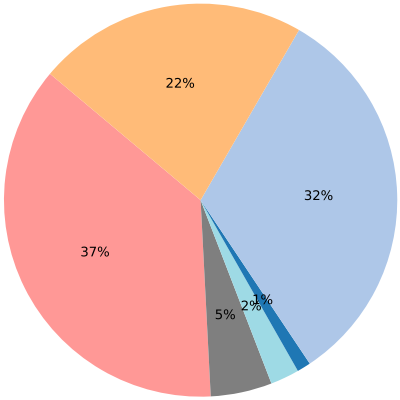
Figure 14: Capacity mix per owner in % of total capacity (total capacity and number of plants in brackets)



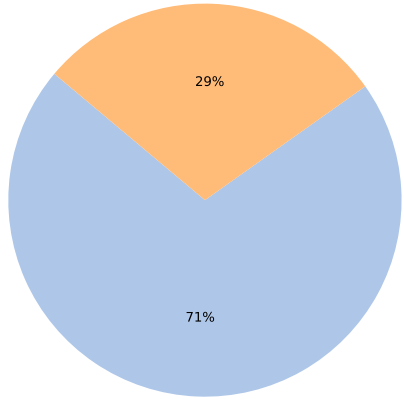
(a) Owner 4 (11.0 GW and 36 plants)



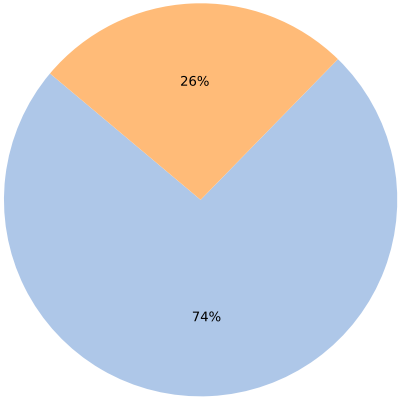
(b) Owner 5 (8.0 GW and 29 plants)



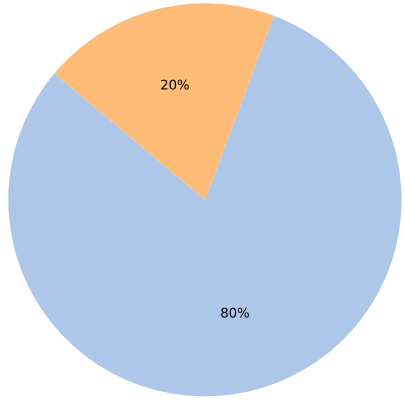
(c) Owner 6 (6.0 GW and 34 plants)



(d) Owner 7 (4.0 GW and 23 plants)



(e) Owner 8 (3.0 GW and 16 plants)



(f) Owner 9 (2.0 GW and 15 plants)

Figure 15: Capacity mix per owner in % of total capacity (total capacity and number of plants in brackets)(continued)