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A multi-scale optimization framework for electricity market participation

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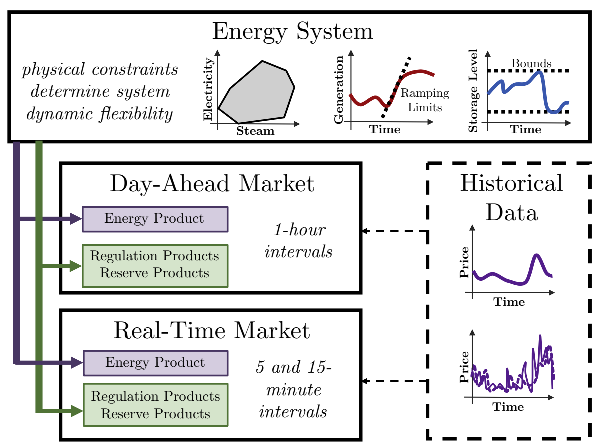
HIGHLIGHTS

- Present framework to assess economic incentives of markets at different timescales.
- Present studies for CHP and battery systems using real CAISO price signals.
- Found that 60–90% of revenue opportunities come from the real-time markets.
- Ancillary service provisions increase revenues by 40–100%.

GRAPHICAL ABSTRACT



Quantify revenue opportunities per market rules and energy system physics

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ABSTRACT

Power grids coordinate a diverse set of energy systems (generators, loads, storage devices) to ensure that supply and demands are matched at multiple timescales (from hours to milliseconds). Such coordination is achieved through hierarchical market transactions. This work presents an optimization framework to evaluate revenue opportunities provided by these multi-scale market hierarchies and to determine optimal participation strategies for individual participants. The proposed framework models day-ahead and real-time transactions of energy, ancillary services, and virtual bidding products provided by independent system operators (ISOs). We apply the framework to a combined heat and power system and a utility-scale battery to determine revenue potential from different market layers and products. Analysis using real price signals for 2015 from the California ISO reveals that 60–90% of the total revenue potential (obtained by participating in all markets) is provided by real-time markets alone (which operate at fast timescales). Our studies also indicate that providing ancillary services (in addition to day-ahead and real-time energy products) increases revenue potential by 40–100%, depending on the physical flexibility of the technology. The proposed framework can be used to identify which market layers and products offer the greatest economic potential for different energy technologies. Our results also highlight that existing techno-economic studies that focus exclusively on day-ahead energy markets (operating at slower timescales) can dramatically undervalue dynamic flexibility.

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1. Introduction

Power grids coordinate a diverse set of energy systems (generators, loads, storage devices) to ensure that supply and demands are matched at multiple timescales (from hours to milliseconds). Such coordination is achieved through hierarchical (multi-scale) market transactions. The proportion of transactions occurring at different timescales is changing as more intermittent and non-dispatchable power is injected into the system. For instance, wind power introduces power injection fluctuations at high frequencies, which require adjustments in fast real-time energy and ancillary services markets (regulation) [1]. Automation architectures for a broad spectrum of electricity generation and consumption systems (e.g., manufacturing building) are currently being re-designed to exploit incentives provided by faster and more volatile energy markets. For example, the Alcoa Point Comfort Power Plant, which is a utility plant that provides electricity and steam to the adjacent aluminum manufacturing facility, re-optimizes its operations every 15 min in response to electricity and natural gas price fluctuations [2]. These new flexibility-oriented automation architectures provide load flexibility to the power grid in exchange for monetary payments or deferred costs. Similarly, large-scale battery systems and building systems are becoming key providers of dynamic flexibility to the power grid [3,4].

1.1. Electricity markets and demand response

Understanding the economic incentives provided by generation and load flexibility requires careful consideration of wholesale electricity market structures and diverse products. Fig. 1 shows the multiscale control structure currently used to balance the power grid. Resources can participate by buying/selling electrical energy and/or providing ancillary services (regulation, reserves). Fig. 2 shows time-varying prices from the California Independent System Operator (CAISO) for three consecutive days. Energy is transacted at three timescales: in the integrated forward market (day-ahead market with 1-h intervals), in the fifteen minute market, and through the real-time dispatch process (5-min intervals). Table 1 lists the different products transacted at each timescale. Histograms for energy prices at different markets are presented in Fig. 3. As can be seen, prices are less volatile in the day-ahead market and the average price is higher. In the real-time market (FMM, RTD) prices are frequently negative and occasionally exceed \$150/MW h. Energy systems with fast dynamics (e.g., flywheels, batteries) can exploit these fast price fluctuations.

Resources (i.e., generators and loads) provide addition flexibility to the hierarchical grid control structure (Fig. 1) via *regulation* and *reserve* ancillary service market products. Generators and loads providing regulation capacity permit the Automatic Generator Control (AGC) layer (run by the ISO or similar grid entity) to adjust their power set-point with a specified range [5]. Depending on the market region, the AGC layer updates load set-points every 2–15 s. The regulation service provider is compensated both for the amount of regulation capacity provided (a load flexible *band* is offered) and the amount of *mileage*, which is the sum of the absolute distance between consecutive load set points. Mileage calculations are illustrated in Fig. 5. Order 755 of the Federal Energy Regulatory Commission (FERC) provides incentives to participants capable of tracking fast changing load set-points. In California, regulation services are procured as two separate products, regulation up and regulation down, depending on the direction of the flexibility band relative to the nominal set-point (from the corresponding energy market). Spinning reserves support regulation service and safeguard against unplanned outages and increased loads. Spinning reserves are rarely dispatched and resources providing reserves are compensated for providing flexibility/contingency. As additional intermittent and non-dispatchable wind and solar power is absorbed, balancing the power grid becomes more challenging due to high-frequency (minute) variations from these sources. As such, requirements for ancillary services are expected to grow. For example, regulation capacity requirements for Texas are anticipated to increase by 10–15% if wind penetration increases from 5000 MW to 15,000 MW [6]. In February 2016, CAISO approximately doubled regulation capacity requirements to account for non-dispatchable renewable sources. As consequence the market price for regulation doubled, resulting in a combined quadrupling of payments to some regulation providers [7]. Finally, reductions in the supply of ancillary services are expected with the retirement of coal-fired generators [8], creating additional opportunities for flexible load providers.

Manufacturing facilities and other large electricity consumers may also participate in electricity markets through Demand Response (DR) programs by manipulating their loads and/or by using on-site generators. DR is typically classified as dispatchable and non-dispatchable, as shown in Fig. 4. For dispatchable DR, the ISO directly controls the load (e.g., balancing authority sends new set points through AGC system to regulation resources), whereas non-dispatchable loads are coordinated through a variety of pricing signals including real-time electricity markets, which are updated every 5–15 min. In Texas, load resources provide 2400 MW of energy and ancillary services, including half of the spinning reserve capacity. To give an idea of the impact of manufacturing, around 1000 MW of this capacity is obtained from a single electrochemical processing facility that provides regulation and other services. Medium (10–50 MW each) and small (less than 10 MW) size industrial/commercial facilities provide the remaining 820 MW and 550 MW of capacity, respectively [8]. The Alcoa facility in Warrick, IN offers several ancillary services in markets run by the Midcontinent ISO. The aluminum smelter provides 70 MW of regulation capacity, which is 15% of its average load (470 MW). This type of operation represents a paradigm shift on the use of manufacturing loads for ancillary services. The same plant also provides 75 MW of interruptible load, which has been dispatched around 55 times per year for an average length of 42 min [10,11]. Alcoa generates up to *120,000* \$*/day of additional revenue by participating in electricity markets*, and has identified potential for 10% energy cost reductions through more targeted operations [10]. Based on data from CAISO, a system providing 10 MW of regulation capacity for every hour in 2015 would have received 500,000 \$/year plus mileage payments. Regulation capacity prices currently reach up to 59 \$/MW and this number might increase as more renewable power is adopted. Moreover, shifting 10 MW of load during the 1% most extreme prices (in the 97 to 1621 \$/MW h range) in the CAISO real-time energy market to the average price (30 \$/MW h) would yield savings of 400,000 \$/yr. The savings for large manufacturing facilities can reach millions of dollars per year. For instance, the pumping system of an oil pipeline comprised of 50 pump units with 6500 horsepower electric motors has a load of 200 MW. Large refineries in Texas have generation facilities of up to 500 MW and usually have excess power capacity installed.[1]

1.2. Literature review

Diverse studies have analyzed market participation of a variety of technologies such as combined heat and power (CHP) plants [12–17], steel furnaces [18,19], cement plants [20–22,14], air separation units [23,24,22,25–27], electrochemical manufacturing facilities [28], HVAC systems for large buildings [29,4,30–32], and

[1] http://www.iaee.org/documents/denver/varela-salazar.pdf.

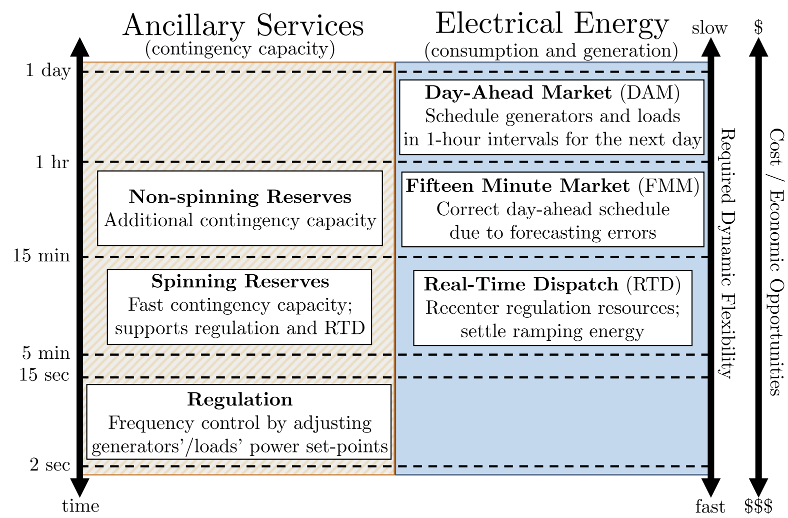


Fig. 1. Multi-scale market-based control hierarchy for the power grid. Resources may participate via multiple ancillary service and energy products (shown as rectangles).

manufacturing systems with thermal energy storage [33]. Most of these studies, however, focus on industrial DR/market participation at scheduling and planning decision layers that consider coarse (e.g., 1 h) time discretizations. Emphasis has been placed on optimal planning under time-varying electricity prices [20,21,19,34,22,16], although recent work considers providing reserve capacity [35,26,36] and interruptible loads [37]. The remainder of this paper argues that these previous analyses underestimate system flexibility and revenue opportunities provided by regulation and real-time energy markets, which operate at fast timescales (seconds and minutes). For instance, significant incentives in regulation markets have been identified for large building systems [29,4,32,31,38]. In particular, [38] compares two control strategies for modulating the fan power consumption to provide regulation at high frequencies (0.03–0.002 Hz) while not interfering with chiller operation. A similar idea can be applied to chemical and other manufacturing facilities where one can exploit mechanical equipment without compromising slower units. Study of demand response from new industrial facilities is very timely as recently a group of power systems experts called for additional techno-economic analysis of alternate demand response sources to better inform market incentives [8].

Many studies have also analyzed the economics of Energy Storage Systems (ESS) such as flywheels [39,40], batteries [39,41,3,42–45,40,46], pumped-hydro [39,41,46], compressed air energy storage [39,46], concentrated solar power generators with thermal energy storage and/or supplemental boiler [47–50], fuel cells [51,41], and other technologies [39,52] interacting in wholesale electricity markets. Approximately half of the reviewed studies focus on only energy arbitrage in day-ahead (forward) markets [39,51,53,54,47,52,50]. Several other papers consider simultaneous sale of energy and ancillary services in the day-ahead market alone [41,49,55,45,40] or analyze only regulation revenues [3,44]. Real-time markets are considered in only five studies [39,56,48,57,46]. In [48], the authors determine that sufficiently volatile real-time markets, such as those in Germany and West Texas, support the installation of electric heaters to "charge" thermal storage systems for concentrated solar power plants during low/negative prices. Bids for energy and reserves from electric vehicle aggregators in day-ahead markets are studied in [57] while real-time prices are only considered to settle reserve dispatches. In [46], the authors compare revenue opportunities for five ESS technologies, and find 37 to 141% higher revenues in Nordic balancing (real-time) markets. The authors, however, consider participation in one market or energy service provision at a time and highlight the need for more sophisticated market participation strategies. Similarly, [39] compares 14 ESS technologies in seven US markets using only real-time prices. [56] analyzes the economics of hybrid energy systems (power cycle plus additional manufacturing systems) in the context of electricity, feedstock, and product (e.g., chemical) markets.

1.3. Key contributions and paper organization

In the context of the reviewed literature, this work addresses the following specific questions:

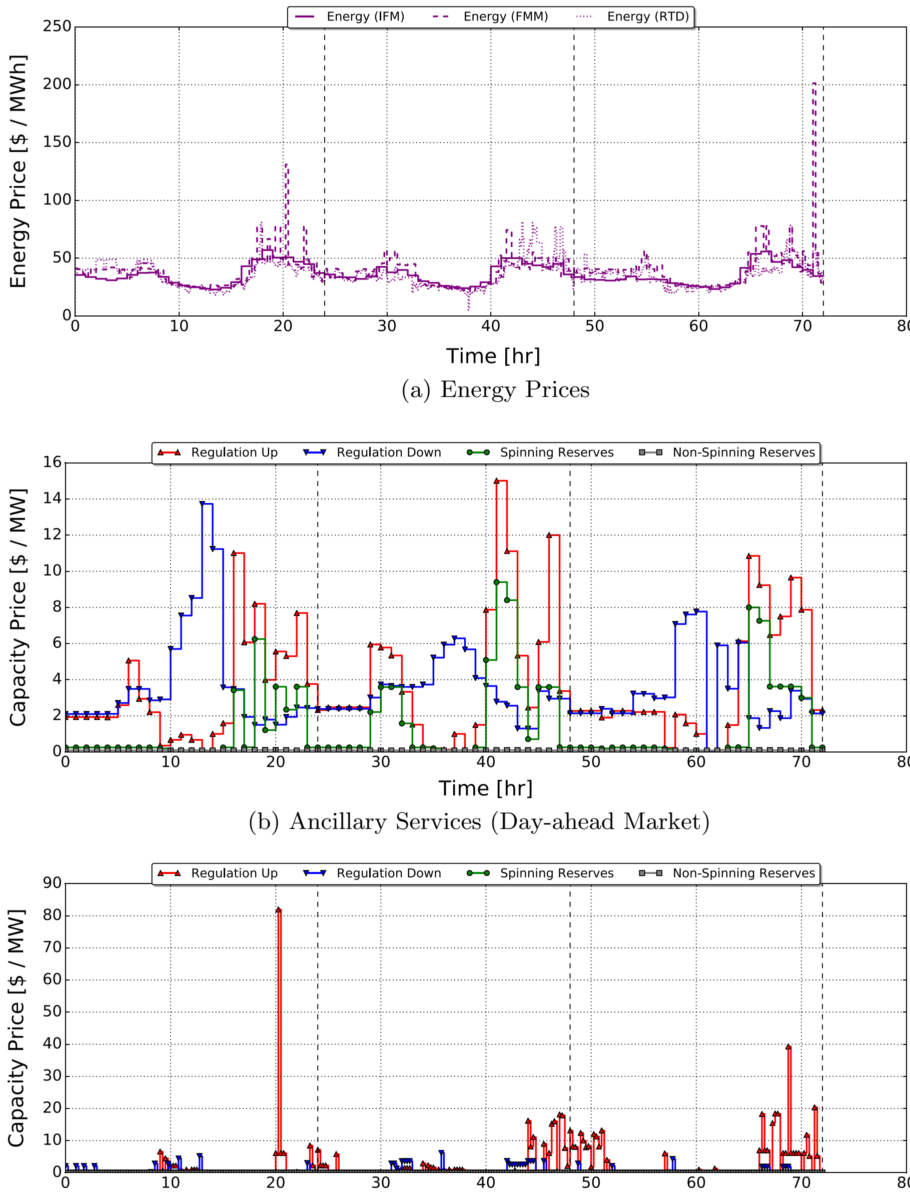
1. What are the economic opportunities provided by energy and ancillary service products offered at different timescales?
2. Which market layers and products offer the greatest economic potential?
3. How do system-specific *physical capacity and dynamic flexibility* aid participation in different layers and improve revenue potential?

To answer these questions, we propose a general multi-scale optimization framework to capture diverse revenue streams provided by wholesale electricity markets. Specifically, the framework models day-ahead and real-time energy, ancillary services, and virtual bidding products provided by ISOs in the United States. Using the framework, we calculate the revenue potential of two energy technologies from historical price signals for all of year 2015 and make two key observations: (1) In California, *62–94% of the total revenue potential* is only accessible via real-time markets. (2) Providing ancillary services can boost revenue potential by 40–100% (relative to energy-only market participation). These results stress the importance of fast flexibility in energy systems and suggest that previous studies that focus on only day-ahead markets and/or energy products underestimate revenues.

The paper is structured as follows. Section 2 discusses electricity market organization and products. Section 3 mathematically describes market rules and presents the multi-scale optimization framework. Sections 4 and 5 analyze revenue streams for a combined heat and power (CHP) system and a utility-scale battery. The paper closes in Section 6 with concluding remarks and directions of future work.

2. Electricity market organization

Wholesale electricity markets, including those operated by CAISO, PJM, Midcontinent ISO, ISO New England, and New York



(a) Energy Prices

(b) Ancillary Services (Day-ahead Market)

(c) Ancillary Services (Real-time Market)

Fig. 2. Energy and ancillary service prices from Daggett, CA for January 1–3, 2015.

ISO in the United States allow for energy transactions at multiple timescales to ensure that supplies match demands at any moment throughout the network. This requires careful coordination of operational schedules for generators and loads while considering transmission network limits, generator capacity limits, and ramping constraints. Markets normally follow a two-settlement system in which a day-ahead market seeks to commit transactions based on expected (forecasted) system performance while a real-time market allows for corrections when the system deviates from expected performance due to forecast errors or contingencies. Market settlements set prices for multiple products and at different times. The locational marginal price (LMP) reflects the marginal cost of serving an additional unit of energy at a specified node in the transmission system, typically with units \$/MW h. This price factors in three components: energy, transmission losses, and congestion. Ancillary service marginal prices (ASMPs) are primarily used in CAISO to compensate ancillary service awards, with additional mechanisms to recover opportunity costs and special pricing rules for shortage situations. Although this manuscript focuses on the structure of markets operated by CAISO, many of the concepts

Table 1
Timescale-product mapping for CAISO markets.

	Day-ahead market	Real-time market	
	Integrated Forward Market (IFM) 1 h	Fifteen Minute Market (FMM) 15 min	Real-Time Dispatch (RTD) 5 min
Energy	✓	✓	✓
Ancillary services			
Regulation down	✓	✓	–
Regulation up	✓	✓	–
Spinning reserves	✓	✓	–
Non-spin. reserves	✓	✓	–

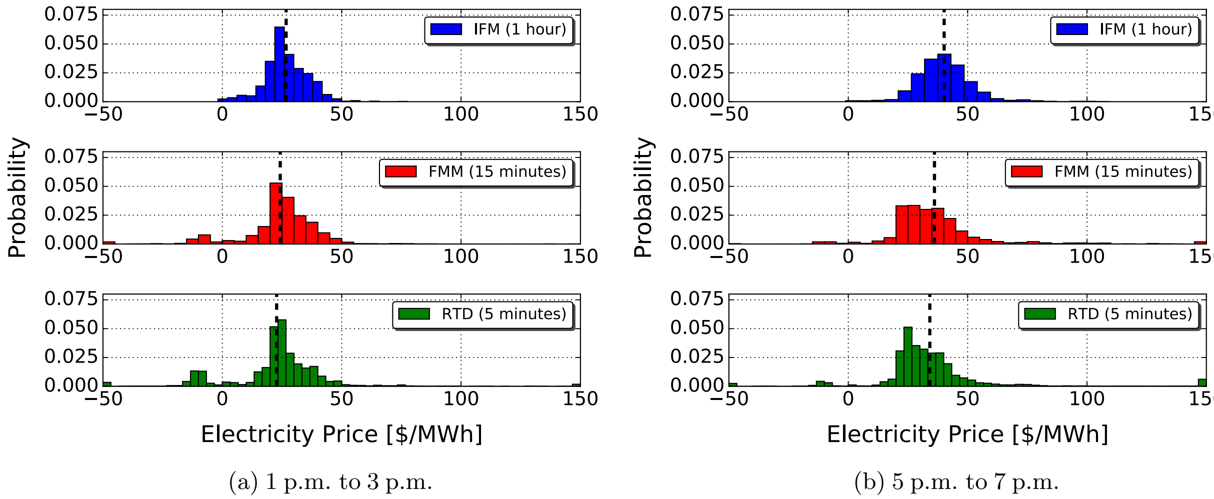


Fig. 3. Histogram of electricity prices for 2015 for a CAISO node near Daggett, CA. Probabilities calculated using a time-weighted average. The dashed lines mark the mean prices for each market (DAM, FMM, RTM). Larger price variations are observed in the fast markets and higher average prices in the day-ahead (hourly) market and during the evening.

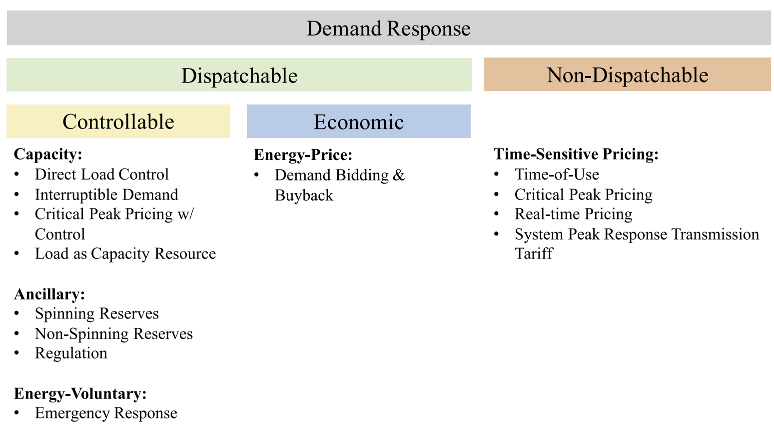


Fig. 4. Classification of Demand Response (DR) modes. Adapted from Fig. 1 in [9].

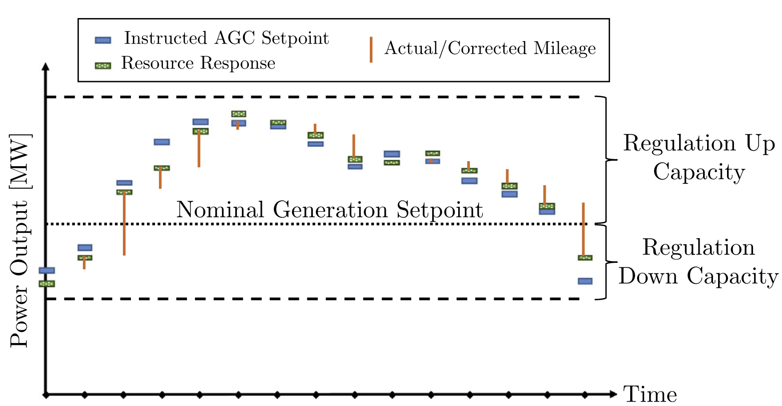


Fig. 5. Illustration of regulation mileage, which is the sum of the "distance" traveled between AGC setpoint signals. Mileage is corrected with actual telemetry to prevent resources from benefiting from under- or overresponse. Each ISO has specific formulas and mileage payment procedures for incentivizing accurate responses.

are applicable to markets in other regions. See [58] for additional background and [59] for a comparison of real-time market structures from around the world.

2.1. Day-ahead markets

The day-ahead market (DAM) seeks to schedule sufficient generation capacity and ancillary services to meet the forecasted demand for the next day. As illustrated in Fig. 6, the CAISO DAM consists of three processes. After bids are submitted (no later than 10 a.m. the day before), they are analyzed in the **Market Power Mitigation** (MPM) process. Due to the physical limits of electricity generation and transport (e.g., transmission and ramping constraints, electrical storage), electricity markets are more susceptible to manipulation by firms with substantial market power compared to other competitive commodity markets [60]. The

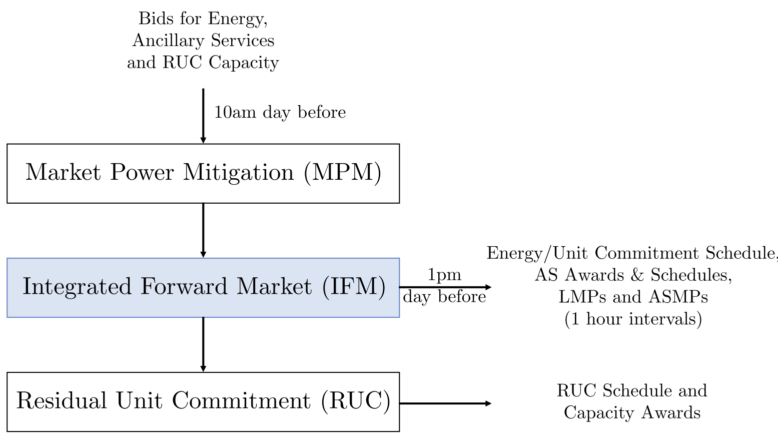


Fig. 6. Structure and timeline of the day-ahead market (DAM) run by CAISO.

MPM process thus seeks to detect and counteract actions inconsistent with competitive markets.

Specifically forbidden practices include (i) withholding physical capacity that would be bid in the absence of market power, (ii) refusing to bid or making unjustifiably high bids to ensure a facility will not be dispatched or to influence LMPs, (iii) increasing electricity generation to cause or obtain benefits from transmission constraints, and (iv) submitting unjustifiably high start-up, bid or minimum load costs, or misrepresenting physical operating capabilities to influence uplift payments. Mitigation is accomplished by solving a security constrained unit commitment (SCUC) problem and decomposing the congestion component of LMPs into competitive and non-competitive parts. Bids with non-competitive congestion components greater than zero are mitigated (i.e., adjusted in accordance with a complex price ceiling). Virtual bids and bids from participating loads, demand response resources and non-generators are considered in the MPM process but not subject to mitigation.

The mitigated and unmitigated bids from the MPM are used as inputs to the **Integrated Forward Market** (IFM), which seeks to determine unit commitment, manage congestion, and establish prices. Another SCUC problem is solved to clear supply bids against bid-in demands and minimize total bid cost while considering transmission limits and technical/operating constraints (e.g., minimum run times). Energy and ancillary service procurement is co-optimized in the IFM, such that sufficient ancillary services are awarded to cover 100% of the forecasted demand. The IFM produces a set of binding hourly day-ahead schedules and ancillary service awards, including hourly LMPs and ASMPs. These results are published no later than 1 p.m. the day before.

Next, in the **Residual Unit Commitment** (RUC) process, additional demand may be procured to ensure sufficient capacity is committed to accommodate demand forecast errors. RUC capacity bids are voluntary and are submitted in conjunction with energy and ancillary bids for the IFM. Virtual RUC bids are not permitted. In order to prevent over procurement in the RUC, CAISO anticipates bids in the real-time market from intermittent resources (e.g., photovoltaics) using historical data.

2.2. Real-time markets

Real-time markets are used to mitigate discrepancies between forecasted and actual demand, unplanned outages, and transmission and generator failures by adjusting energy and ancillary service schedules and procuring additional capacity. The RTM structure is more complex than that of the DAM, as shown in Fig. 7. Energy and ancillary service bids must be submitted at least 75 min before the start of each trading hour. After the **Market Power Mitigation** (MPM) process, the bids are used in the **Hour Ahead Scheduling Process** (HASP) to establish binding inter-tie schedules (links to transmission systems outside CAISO) and to provide *advisory* prices and schedules. This advisory data informs operational plans and bidding strategies for subsequent hours. Every 15 min, the **Real-Time Unit Commitment** (RTUC) runs and dispatches additional fast and short start resources. The results are used by the **Fifteen Minute Market** (FMM) to establish binding schedules and prices for energy (LMPs) and ancillary services (ASMPs) for 15-min intervals. Once every hour the **Short-Term Unit Commitment** process is run to dispatch additional short and medium start resources. Finally, every 5 min, the **Real-Time Dispatch** process schedules additional energy and sets 5-min energy prices (LMPs). The FFM and RTD layers set real-time prices.

Real-time markets are implemented as intricate layers of optimization problems. The RTUC solves a Security Constrained Unit Commitment (SCUC) problem over a horizon of four to seven 15-min intervals. Fig. 8 presents the timing of the RTUC processes. One RTUC run is started every 15 min. The HASP corresponds to the RTUC run started 7.5 min before the beginning of each trading hour. The FMM is settled using results for the second interval of each RTUC horizon. As such, FMM settlements are based on the data available 37.5 min before each 15-min interval (see Fig. 8). This structure introduces errors from lag, and necessitates a faster layer; the RTD runs 7.5 min before the start of each 5 min interval, and solves a Security Constrained Economic Dispatch (SCED) problem. It establishes binding energy prices and schedules for the next interval and advisory information for subsequent intervals in the trading hour. Medium start units are scheduled once each hour in the STUC process, which solves a SCUC problem with a planning horizon of approximately 5 h.

2.3. Energy settlements

Payment for energy is settled using the LMPs from the corresponding market. Thus, energy procured in the IFM is settled using LMPs from the IFM. *Imbalance energy* is the difference between energy schedules from different markets. For example, if a resource is scheduled to deliver energy via the IFM, but the schedule is modified in the FMM, the difference is known as *FMM instructed imbalance energy* and is settled with the FMM LMPs. *RTD instructed imbalance energy* is similarly defined and is settled with RTD LMPs. This is important as the IFM schedule, which considers energy output in constant 1-h intervals, does not consider ramping energy, which is a form of imbalance energy. If a resource fails to meet its scheduled energy production/consumption for unanticipated reasons, the deviation is known as *RTD uninstructed imbalance energy*, and is settled using RTD LMPs.

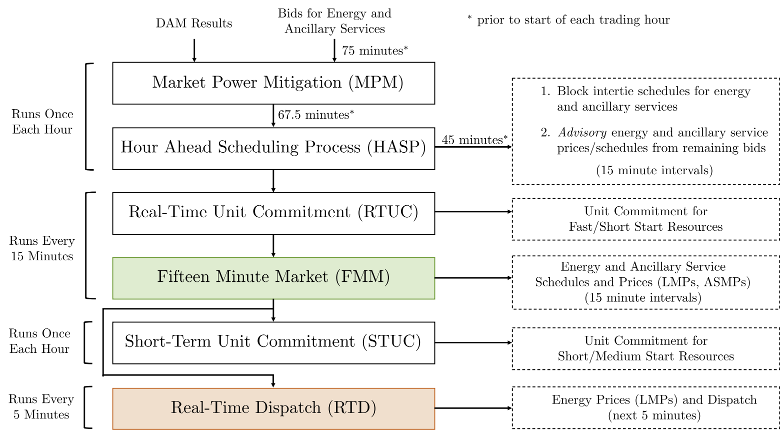


Fig. 7. Structure and timeline of the real-time markets (RTM) run by CAISO.

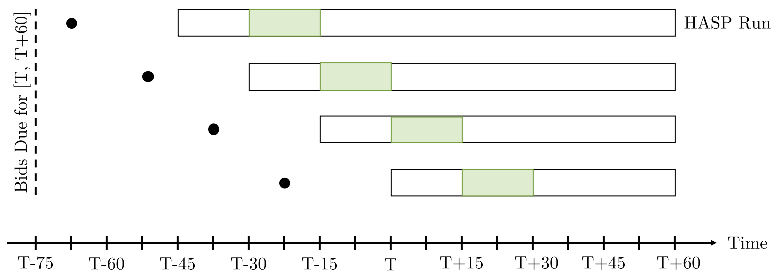


Fig. 8. Timeline for the Real-Time Unit Commitment (RTUC) process. Four different instances are shown. The black circles mark when each RTUC process starts, with time T corresponding to the start of the reference trading hour. The long rectangles show the planning horizon used for each RTUC process. The shaded (green) regions mark the part of each RTUC result used to settle the FMM (i.e., are financially binding). The HASP is a special instance of the RTUC, and corresponds to the run started before each hour. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

3. Multi-scale optimization model

This section describes the components of the multi-scale optimization framework that include time discretization, market products, general physical constraints, and operational logic. The subsequent sections illustrate how to tie this general framework to specific energy technologies.

3.1. Time discretization

The multi-layered time discretization scheme illustrated in Fig. 9 captures product sales and purchases at multiple timescales. The modeling framework is flexible in that it can capture an arbitrary number of layers and time resolutions at each layer. For CAISO, level 0 denotes a day of operation, level 1 comprises one-hour time intervals in the day-ahead market (i.e., $N_1 = 24$), level 2 corresponds to the fifteen-minute market (i.e., $N_2 = 4$), and level 3 contains five-minute (real-time) market ($N_3 = 3$). It should be noted that the time discretization currently used in CAISO is rather arbitrary and can potentially change in the future as, for example, a day-ahead market can in principle use resolutions of less than an hour and the real-time market could use resolutions of ten minutes or less than 5 min.

Consider the sets of *time intervals* $\mathcal{T}_\ell := \{1,\ldots,N_\ell\}$ where ℓ indicates the market layer and $\ell \in \mathcal{L} := \{3,2,1,0\}$. Let Δt_ℓ denote the length of the time interval in layer $\ell \in \mathcal{L}$ (units of hours). The lexicographic time set

$$\begin{aligned}\mathcal{T}^* &:= \mathcal{T}_{|\mathcal{L}|} \times \cdots \times \mathcal{T}_2 \times \mathcal{T}_1 \times \mathcal{T}_0 \\ &= \{(1,1,1,1),(2,1,1,1),\ldots, \\ &\quad (N_3,1,1,1),(1,2,1,1),\ldots,(N_3,N_2,1,1),\ldots,(N_3,N_2,N_1,N_0)\},\end{aligned} \tag{3.1}$$

captures the hierarchical nature of the time discretization. Lexicographic time sets for individual layers are similarly defined: $\mathcal{T}_3^* := \mathcal{T}^*,\ \mathcal{T}_2^* := \mathcal{T}_2 \times \mathcal{T}_1 \times \mathcal{T}_0,\ \mathcal{T}_1^* := \mathcal{T}_1 \times \mathcal{T}_0$, and $\mathcal{T}_0^* = \mathcal{T}_0$. Next, consider a *time instant t* (corresponding to physical time) that is compatible with the time interval of the fastest timescale. Such instance t is defined by the tuple (i_3,i_2,i_1,i_0) and corresponds to the nested indexes $t_3^*(t) = t = (i_3,i_2,i_1,i_0),\ t_2^*(t) = (i_2,i_1,i_0)$, $t_1^*(t) = (i_1,i_0)$, and $t_0^*(t) = i_0$. Thus $t_3^*(t) \in \mathcal{T}_3^*,\ t_2^*(t) \in \mathcal{T}_2^*,\ t_1^*(t) \in \mathcal{T}_1^*$, and $t_0^*(t) \in \mathcal{T}_0^*$ for any $t \in \mathcal{T}_3^*$. The notation $t+1$ is used to indicate a forward (lexicographic) step in an element of the set $\mathcal{T}_3^*$ and we use similar notation for the rest of the lexicographic sets. This nested time discretization representation can be used for an arbitrary number of layers.

As previously discussed, in electricity markets the same product (e.g., energy or ancillary services) can be sold or bought at different market layers. A common character (e.g., E) is used to represent a given product (e.g., energy) with the index indicating the corresponding market layer. For instance, $\bar{E}_{t_3^*(t)}$ corresponds to the energy sales in the third market layer at time instant $t_3^*(t) = t \in \mathcal{T}_3^*$ while $\bar{E}_{t_1^*(t)}$ corresponds to energy sales in the first market layer at time interval $t_1^*(t) \in \mathcal{T}_1^*$. The proposed nested index notation facilitates the expression of several quantities of interest. For instance, the quantity $\sum_{\ell\in\mathcal{L}} \bar{E}_{t_\ell^*(t)}$ represents the total energy sold at time instant t at all market layers.

3.2. Products and net energy

Consider a generic energy system capable of selling and purchasing energy and selling ancillary services at multiple timescales. Let $\bar{E}_{t_\ell^*(t)}$ and $\underline{E}_{t_\ell^*(t)}$ represent the average power sold and

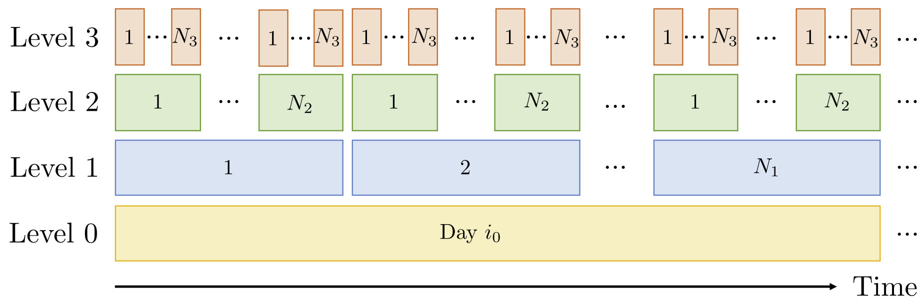


Fig. 9. Four-layer time discretization representation.

purchased at market level ℓ, respectively. Similarly, let $A_{a,t^*_\ell(t)},\ a \in \mathcal{A} := \{s, n, r^+, r^-\}$ represent the ancillary service capacity provided in the same market level for the spinning reserves (s), non-spinning reserves (n), regulation up (r^+), and regulation down (r^-) ancillary services. The energy system is assumed to be capable of satisfying onsite demand $\hat{E}_{t^*_3(t)}, t \in \mathcal{T}^*$. Let $E_{t^*_3(t)}$ represent the average net power:

$$E_{t^*_3(t)} = \hat{E}_{t^*_3(t)} + \sum_{\ell \in \mathcal{L}} \left(\bar{E}_{t^*_\ell(t)} - \underline{E}_{t^*_\ell(t)} \right), \quad t \in \mathcal{T}^*. \tag{3.2}$$

All of these quantities are normalized using the nameplate capacity Λ^E. Consequently, $0 \leqslant A_{t^*_\ell(t)}, \bar{E}_{t^*_\ell(t)}, \underline{E}_{t^*_\ell(t)}, \hat{E}_{t^*_\ell(t)} \leqslant 1$. The bounds for net energy depend on the technology specific physics: $0 \leqslant E_{t^*_\ell(t)} \leqslant 1$ for systems that only net produce electricity (e.g., conventional thermal generators) and $-1 \leqslant E_{t^*_\ell(t)} \leqslant 1$ for other energy systems capable of both producing and consuming electricity (e.g., batteries, flywheels).

3.3. Revenues

Net energy revenues (R_E) are given by the difference between energy sales and purchases accumulated over all time intervals:

$$R_E = \Lambda^E \sum_{t \in \mathcal{T}^*} \sum_{\ell \in \mathcal{L}} \Delta t_\ell \pi^E_{t^*_\ell(t)} \left(\bar{E}_{t^*_\ell(t)} - (1+\epsilon) \underline{E}_{t^*_\ell(t)} \right), \tag{3.3}$$

where $\pi^E_{t^*_\ell(t)}$ represents the price for energy in market level ℓ during time interval $t^*_\ell(t)$. This assumes that the energy system receives no external revenue for satisfying onsite electricity demand. In many wholesale markets, including CAISO, the simultaneous sale and purchase of energy is permitted. In fact, purchasing energy on one market (e.g., day-ahead) and reselling it on another (e.g., real-time) at the same time is a common practice known as *virtual bidding* (discussed later on). Because a single price is used for both energy sales and purchases at each market level, it is possible for the solutions to be degenerate (non-unique). This is prevented by modifying the price of energy purchases by a factor $\epsilon > 0$. In this work, $\epsilon = 10^{-6}$. Eq. (3.3) can be easily modified to accommodate wholesale markets with separate energy prices for sales and purchases.

Net revenue for ancillary services, denoted byR_A, is calculated as:

$$R_A = \Lambda^E \sum_{a \in \mathcal{A}} \sum_{t \in \mathcal{T}^*} \sum_{\ell \in \mathcal{L}} \left(\pi^A_{a,t^*_\ell(t)} A_{a,t^*_\ell(t)} \right), \tag{3.4}$$

where $A_{a,t^*_\ell(t)}$ is the amount of ancillary service capacity for product a sold into market level ℓ during timestep $t^*_\ell(t)$. Regulation revenues only include capacity payments, and it is assumed the mileage payments exactly offset the cost of tracking the regulation signal. In CAISO, energy is transacted on three timescales (hour, 15 min, 5 min) whereas ancillary services are only procured on two timescales (hour, 15 min). Thus $A_{a,t^*_3(t)} = 0,\ t \in \mathcal{T}^*$ for energy systems interacting with CAISO markets.

3.4. Ramping limits

The net power on all three levels between timesteps is bounded by the ramp rate $\rho^E > 0$:

$$-\rho^E \Delta t_3 \leqslant E_{t^*_3(t)} - E_{t^*_3(t-1)} \leqslant \rho^E \Delta t_3, \quad t \in \mathcal{T}^*. \tag{3.5}$$

As expected, the larger ρ^E is, the more dynamic flexibility the system provides. Because $t^*_3(t) = t$ holds, the above equation is equivalent to:

$$-\rho^E \Delta t_3 \leqslant E_t - E_{t-1} \leqslant \rho^E \Delta t_3, \quad t \in \mathcal{T}^*. \tag{3.6}$$

3.5. Ancillary service capacity

(Non)-spinning reserve capacity is restricted to be between 0 and 1. Regulation up and down capacity is asymmetric and restricted by the bounds ρ^{max}_+ and ρ^{max}_-:

$$0 \leqslant s_{t^*_\ell(t)}, n_{t^*_\ell(t)} \leqslant 1, \quad \ell \in \mathcal{L}, \quad t \in \mathcal{T}^*, \tag{3.7}$$

$$0 \leqslant r^+_{t^*_\ell(t)} \leqslant \rho^{max}_+, \quad \ell \in \mathcal{L}, \quad t \in \mathcal{T}^*, \tag{3.8}$$

$$0 \leqslant r^-_{t^*_\ell(t)} \leqslant \rho^{max}_-, \quad \ell \in \mathcal{L}, \quad t \in \mathcal{T}^*. \tag{3.9}$$

The previous equations represent general physical constraints that will limit transactions of energy and regulation products by any market participant. The following constraints are specific to certain types of participants.

3.6. Generating systems

For generators with significant start-up and shut-down times/costs, it is necessary to model the operational mode. In CAISO, it is permissible to simultaneously sell energy, regulation, and reserves. Similarly, when the generator is spinning mode, it is permissible to sell both spinning and non-spinning reserves as long as capacity is not double-counted. Under these rules, a generator may operate in one of three modes: (i) generating, (ii) spinning, and (iii) not spinning. The binary variables y^e, y^s and y^n represent these three modes, respectively. Such decisions are made on an hourly basis:

$$y^e_{t^*_1(t)},\ y^s_{t^*_1(t)},\ y^n_{t^*_1(t)} \in \{0,1\}, \quad t \in \mathcal{T}^*. \tag{3.10}$$

When the generator is in *generation* mode, the market allows the system to sell regulation capacity provided that the total regulation capacity does not exceed ρ^{max}_{reg}:

$$\sum_{\ell\in\mathcal{L}}\left(r^{+}_{t^*_\ell(t)}+r^{-}_{t^*_\ell(t)}\right)\leqslant\rho^{max}_{reg}y^{e}_{t^*_1(t)},\quad t\in\mathcal{T}^*. \tag{3.11}$$

In CAISO, the ramp capability for 10 min limits both the total regulation capacity and the sum of regulation up, spinning reserves, and non-spinning reserves. Consequently, $\rho^{max}_{reg}=\rho^{max}_{+}=\rho^{max}_{-}=\rho^{E}\frac{10\text{ min}}{60\text{ min/h}}$ and the following constraint is imposed:

$$\sum_{\ell\in\mathcal{L}}\left(r^{+}_{t^*_\ell(t)}+s_{t^*_\ell(t)}+n_{t^*_\ell(t)}\right)\leqslant\rho^{max}_{reg},\quad t\in\mathcal{T}^*. \tag{3.12}$$

Similarly, the maximum generation capacity may not be exceeded, which prevents capacity double-counting. This is modeled as:

$$E_{t^*_3(t)}+\sum_{\ell\in\mathcal{L}}\left(r^{+}_{t^*_\ell(t)}+s_{t^*_\ell(t)}+n_{t^*_\ell(t)}\right)\leqslant 1,\quad t\in\mathcal{T}^*. \tag{3.13}$$

Let Λ represent the minimum operating capacity. If $\Lambda>\rho^{E}\Delta t_3$, then (3.5) must be relaxed to ensure that start-up is feasible. Recall that $t^*_1(t^*_3(t))=t^*_1(t)$ and define

$$z_{t^*_3(t)}:=\rho^{E}\Delta t_3+\max(|t^*_1(t)-t^*_1(t-1)|,1)\times(1-\rho^{E}\Delta t_3)(2-y^{e}_{t^*_1(t)}-y^{e}_{t^*_1(t-1)}). \tag{3.14}$$

Thus (3.5) can be relaxed using the constraint:

$$-z_{t^*_3(t)}\leqslant E_{t^*_3(t)}-E_{t^*_3(t-1)}\leqslant z_{t^*_3(t)},\quad t\in\mathcal{T}^*. \tag{3.15}$$

Let θ_r represent the fraction of onsite demand that may be used for regulation. While the system is in *generation mode*, the net generation must be greater than Λ plus R (the amount of awarded regulation down capacity not covered by onsite demand):

$$R_{t^*_3(t)}\geqslant 0,\quad R_{t^*_3(t)}\geqslant\left(\sum_{\ell\in\mathcal{L}}r^{-}_{t^*_\ell(t)}\right)-\theta_r\hat{E}_{t^*_3(t)},\quad t\in\mathcal{T}^*, \tag{3.16}$$

$$E_{t^*_3(t)}\geqslant\Lambda^{E}y^{e}_{t^*_1(t)}+R_{t^*_3(t)},\quad t\in\mathcal{T}^*. \tag{3.17}$$

When ($\theta_r=1$), the onsite demand is completely flexible and its entire capacity may be used for regulation down. Regulation up capacity is restricted to the amount of energy sales plus the amount of regulation-suitable onsite demand:

$$\theta_r\hat{E}_{t^*_3(t)}+\sum_{\ell\in\mathcal{L}}\bar{E}_{t^*_\ell(t)}\geqslant\sum_{\ell\in\mathcal{L}}r^{+}_{t^*_\ell(t)},\quad t\in\mathcal{T}^*. \tag{3.18}$$

Spinning reserve sales are permitted in modes *i* and *ii*:

$$\sum_{\ell\in\mathcal{L}}s_{t^*_\ell(t)}\leqslant y^{e}_{t^*_1(t)}+y^{s}_{t^*_1(t)},\quad t\in\mathcal{T}^*. \tag{3.19}$$

Non-spinning reserves sales are permitted in all three modes:

$$\sum_{\ell\in\mathcal{L}}n_{t^*_\ell(t)}\leqslant y^{e}_{t^*_1(t)}+y^{s}_{t^*_1(t)}+y^{n}_{t^*_1(t)},\quad t\in\mathcal{T}^*. \tag{3.20}$$

Finally, only one mode of operation is permitted at a given time:

$$y^{e}_{t^*_1(t)}+y^{s}_{t^*_1(t)}+y^{n}_{t^*_1(t)}\leqslant 1,\quad t\in\mathcal{T}^*. \tag{3.21}$$

The use of binary variables in the proposed model is necessary to capture the logic of market participation. For example, if a generator is currently operating at its minimum capacity then it cannot offer regulation down capacity. In addition, binary variables can be used with other mode detailed models to restrict on/off schedules (e.g., enforce minimum up and down times), such as [61,62,54].

3.7. Non-generating systems

Systems that do not generate electricity (e.g., batteries, flywheels, or buildings) are not subjected to the constraints of Section 3.6. With sufficient capacity, these systems are capable of providing regulation with zero net energy sales. For these systems, the following constraints replace (3.10)–(3.21), and are derived by setting $y^e=1$ and $\Lambda=-1$.

$$\sum_{\ell\in\mathcal{L}}\left(r^{+}_{t^*_\ell(t)}+r^{-}_{t^*_\ell(t)}\right)\leqslant\rho^{max}_{reg},\quad t\in\mathcal{T}^* \tag{3.22}$$

$$\sum_{\ell\in\mathcal{L}}\left(r^{+}_{t^*_\ell(t)}+s_{t^*_\ell(t)}+n_{t^*_\ell(t)}\right)\leqslant\rho^{max}_{reg},\quad t\in\mathcal{T}^* \tag{3.23}$$

$$R_{t^*_3(t)}-E_{t^*_3(t)}\leqslant 1,\quad t\in\mathcal{T}^* \tag{3.24}$$

$$R_{t^*_3(t)}\geqslant 0,\quad R_{t^*_3(t)}\geqslant\left(\sum_{\ell\in\mathcal{L}}r^{-}_{t^*_\ell(t)}\right)-\theta_r\hat{E}_{t^*_3(t)},\quad t\in\mathcal{T}^* \tag{3.25}$$

$$E_{t^*_3(t)}+\sum_{\ell\in\mathcal{L}}\left(r^{+}_{t^*_\ell(t)}+s_{t^*_\ell(t)}+n_{t^*_\ell(t)}\right)\leqslant 1,\quad t\in\mathcal{T}^*. \tag{3.26}$$

The proposed model allows non-generating systems to buy and sell energy while simultaneously providing ancillary services. The model does not consider special designations available in some wholesale markets. For example, in CAISO, energy storage systems may choose to participate in *Regulation Energy Management*. Such resources are restricted to only provide regulation, but buy and sell the energy necessary for regulation on the real-time market. The market allows them to bid as regulation capacity (MW) up to four times the energy (MW h) they can curtail or discharge in 15 min.

3.8. Virtual bidding

Virtual bidding is an important financial mechanism in which energy is purchased in one market (either the IFM or FMM) and sold in another market. With a virtual supply award, the bidding entity is paid for energy at the IFM LMP but is charged the cost of energy per the FMM LMP (averaged for the hour). Similarly, with a virtual demand award, the bidder is charged the LMP from the IFM and paid using the LMP from the FMM. These bids are called virtual because they do not involve any physical equipment. In our framework, virtual bids can be modeled concisely as:

$$\bar{E}_{t^*_1(t)}=\underline{E}_{t^*_2(t)},\quad t\in\mathcal{T}^* \tag{3.27}$$

$$\underline{E}_{t^*_1(t)}=\bar{E}_{t^*_2(t)},\quad t\in\mathcal{T}^* \tag{3.28}$$

$$\bar{E}_{t^*_3(t)}=\underline{E}_{t^*_3(t)}=0,\quad t\in\mathcal{T}^*. \tag{3.29}$$

We emphasize that the proposed multi-layered discretization model facilitates the imposition of this type of virtual bidding logic, in which certain products are simply transferred from one time scale to another. Virtual bids are only applicable to energy products and do not involve physical equipment. Consequently, constraints (3.2) and (3.4)–(3.26) are not considered in this case.

4. Case study: combined heat and power system

Combined heat and power (CHP) systems provide electrical and heat energy to buildings or manufacturing facilities. Some CHP systems do not interact directly with the ISO market but instead purchase power directly from a utility company, load aggregator, or other entity. Regardless of the connection mechanism, the exchange of electrical energy with the power grid helps synchronize steam and electricity demands (the time demand profiles of these two products), which are usually out of phase [63]. This first case study quantifies the revenue opportunities from CHP systems interacting directly with the ISO and assess how physical flexibility benefits CHP systems. This is done by coupling the equations from Section 2 (market rules) with mathematical models for CHP system physics. Out of simplicity, special (optional) CAISO rules to ensure steam availability (via must-run levels) and accommodate distinct operating modes (via multi-stage generation classifications) are ignored and the CHP system is treated as a standard thermal generator.

The remainder of this subsection develops a minimalistic mathematical model to represent the physical behavior and flexibility of a CHP system. The proposed framework is general purpose, and compatible with more sophisticated models, such as those in [16,64].

Let $f_{t_3^*(t)}$, $\hat{s}_{t_3^*(t)}$, and $\hat{E}_{t_3^*(t)}$ represent fuel usage, delivered onsite steam, and delivered onsite electricity at time $t \in \mathcal{T}^*$. Furthermore, steam and electricity variables are scaled by their nameplate capacities Λ^{steam} and Λ^E, respectively:

$$0 \leqslant f_{t_3^*(t)}, \quad 0 \leqslant \hat{s}_{t_3^*(t)} \leqslant 1, \quad 0 \leqslant \hat{E}_{t_3^*(t)} \leqslant 1, \quad t \in \mathcal{T}^*. \tag{4.30}$$

Assume that the energy efficiency of the CHP unit is characterized by three parameters: maximum steam efficiency (η^{steam}), maximum electrical efficiency (η^E), and maximum overall energy efficiency (η^{total}). Using these parameters, the fuel usage is bounded as follows:

$$f_{t_3^*(t)} \geqslant \frac{\Lambda^{steam}\hat{s}_{t_3^*(t)} + \Lambda^E E_{t_3^*(t)}}{\eta^{total}}, \quad t \in \mathcal{T}^* \tag{4.31}$$

$$f_{t_3^*(t)} \geqslant \frac{\Lambda^{steam}\hat{s}_{t_3^*(t)}}{\eta^{steam}}, \quad t \in \mathcal{T}^* \tag{4.32}$$

$$f_{t_3^*(t)} \geqslant \frac{\Lambda^E E_{t_3^*(t)}}{\eta^E}, \quad t \in \mathcal{T}^*. \tag{4.33}$$

Assume that the operating range of the CHP unit (feasible pairing of steam and electricity generation levels) may be characterized by a polyhedral region:

$$a\hat{s}_{t_3^*(t)} + bE_{t_3^*(t)} \geqslant c, \quad t \in \mathcal{T}^*, \tag{4.34}$$

where a, b and c characterize the edges of the polyhedron. Fig. 10 shows the assumed operating range overlayed onto the overall energy efficiency for $\eta^{steam} = 45\%$, $\eta^E = 40\%$, and $\eta^{total} = 70\%$.

Assume that the steam generation ramp rate is bounded by ρ^{steam}:

$$-\Delta t_3 \rho^{steam} \leqslant \hat{s}_{t_3^*(t)} - \hat{s}_{t_3^*(t-1)} \leqslant \Delta t_3 \rho^{steam}, \quad t \in \mathcal{T}^*. \tag{4.35}$$

Let $\phi^s_{t_3^*(t)}$ and $\phi^e_{t_3^*(t)}$ represent the *on-site* steam and electrical demands at time $t_3^*(t)$ that the CHP system seeks to satisfy. Furthermore, let θ_s and θ_e represent the fraction of these demands that are flexible, defined as:

$$\phi_{t_3^*(t)}(1-\theta_e) \leqslant \hat{E}_{t_3^*(t)} \leqslant \phi_{t_3^*(t)}(1+\theta_e), \quad t \in \mathcal{T}^*, \tag{4.36}$$

$$\sigma_{t_3^*(t)}(1-\theta_s) \leqslant \hat{s}_{t_3^*(t)} \leqslant \sigma_{t_3^*(t)}(1+\theta_s), \quad t \in \mathcal{T}^*, \tag{4.37}$$

while satisfying the full demands for each day $i_0 \in \mathcal{T}_0^*$:

$$\sum_{t \in \mathcal{T}: t_0^*(t) = i_0} \left(\hat{E}_{t_3^*(t)} - \phi_{t_3^*(t)}\right) = 0, \quad i_0 \in \mathcal{T}_0^*, \tag{4.38}$$

$$\sum_{t \in \mathcal{T}: t_0^*(t) = i_0} \left(\hat{s}_{t_3^*(t)} - \sigma_{t_3^*(t)}\right) = 0, \quad i_0 \in \mathcal{T}_0^*. \tag{4.39}$$

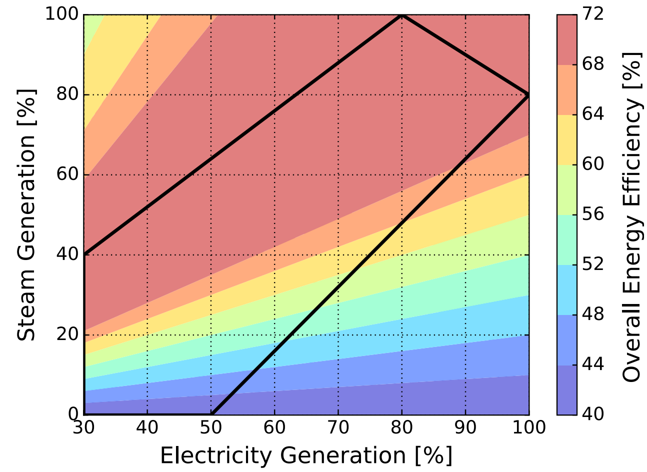


Fig. 10. Overall energy efficiency for CHP system based on the steam and electricity output. Operation is restricted to black polygon.

The fuel costs are calculated as:

$$C_{fuel} = \pi^{fuel} \Delta t_3 \sum_{t \in \mathcal{T}^*} f_{t_3^*(t)}, \tag{4.40}$$

where the price of fuel (π^{fuel}) is assumed to be constant.

The operating policy of the CHP system is optimized to minimize the net operating costs $C_{fuel} - R_E - R_A$, subject to the market rules (3.2)–(3.21), and system model (4.30)–(4.40). Real CAISO settlement prices for all of the year 2015 are used in the analysis. The nominal time demand profiles shown in Fig. 11 is assumed for each day, with the CHP system always running ($y^e_{t_1^*(t)} = 1$ and $y^s_{t_1^*(t)} = y^n_{t_1^*(t)} = 0$). The resulting linear programming problems include up to 200,000 equality constraints, 1.8 million inequality constraints, and 1 million bounded continuous variables for an entire year. Nevertheless, Gurobi solved each problem instance in a few minutes and on a standard workstation. In the context of real-time control and bidding, a much shorter horizon (e.g., days) would likely be considered, reducing the problem size by a factor of 100.

The remaining subsections quantify the benefits of market participation with respect to net operating costs and consider the impact of fuel price, demand flexibility, and different restrictions of market participation. Unless otherwise noted, let $\pi^f = 4$ \$/MBtu, $\theta_s = \theta_e = \theta_r = 0$, $\Lambda^E = \Lambda^{steam} = 1$ MW, $\rho^{steam} = 1.0$ (100% per hour), $\rho^E = 1.8$ (3% per minute as is typical for Rankine cycles [65]), prohibit energy purchases $\left(\underline{E}_{t_\ell^*(t)} = 0\right)$, and permit simultaneous participation in day-ahead and real-time markets.

4.1. Fuel price sensitivity

The first study quantifies the sensitivity of net operating costs to fuel price variability under *four different market participation schemes*: no market participation, sales of energy, sales of energy and regulation, and sales of all products. With low fuel prices (3.0 \$/MBtu), market participation reduces the net operating costs by 49,000 \$/year (for 1 MW steam and electricity capacity), or 59.1% relative to no market participation, as shown in Fig. 12. This is realized by revenues of 89,400 \$/year from market participation and 40,400 \$/year additional fuel costs. Thus *74% of the net savings are realizable with only energy sales*. Providing spinning reserves in addition to regulation and energy had a negligible impact on net operating costs. With high fuel prices (7.0 \$/MBtu), the net operating cost savings are more modest, 25,700 \$/year, with 40,000 \$/

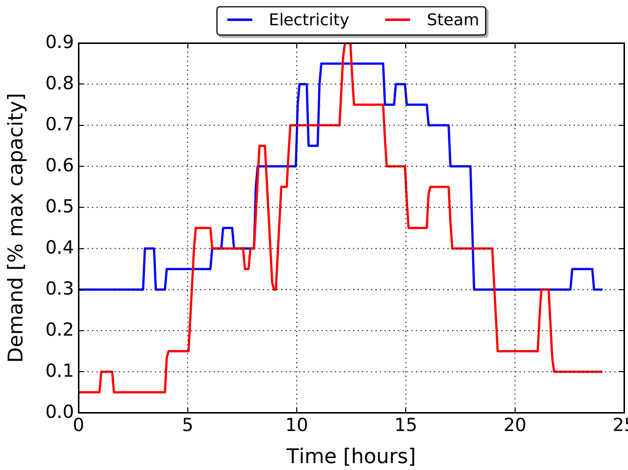
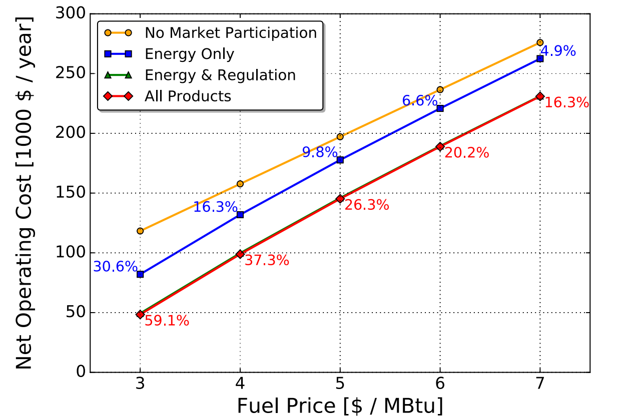
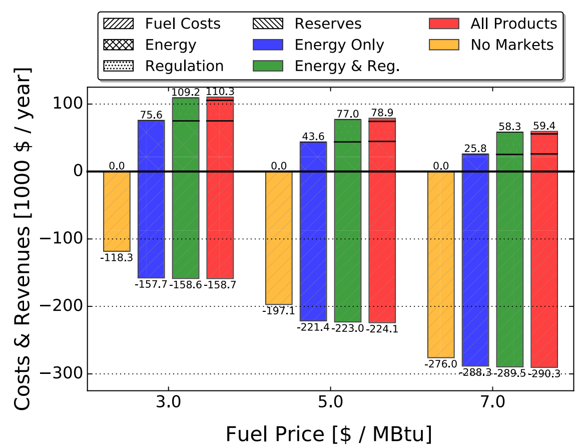


Fig. 11. Nominal steam and electricity demand profiles for CHP system.



(a) Lines indicate net operating cost and numbers are the percent reduction relative to no market participation.



(b) Breakdown of revenue by product type

Fig. 12. Net CHP operating costs as a function of fuel price and market participation mode. Around 4.9–30.6% operating cost reductions are obtained through energy sales using excess capacity. Around 16.3–59.1% cost reductions are obtained through sales of energy and ancillary services.

year in market revenues offsetting the 14,300 $/year increase in fuel consumption. Approximately one-third of these savings are from energy sales, and the remainder is from regulation capacity. Interestingly, the incremental benefit from regulation sales is approximately 12,000 $/year and is insensitive to fuel price.

Fig. 13 shows the operating profiles for January 1st–3rd and highlights the difference between the different market participation modes. The yellow[2] (dotted) region correspond to electricity generation used to meet on-site electricity demand. The purple (crossed) regions correspond to energy sold in the market. Regulation down (blue region) overlaps energy production. Regulation up, spinning reserves and non-spinning reserves are shown in red, green and black, respectively. The solid black line shows the nominal power output level. As can be seen, profiles follow non-trivial patterns, highlighting the need for systematic optimization. In particular, note that the system capacity is almost fully exploited under full market participation by providing all types of products. In other words, capacity is severely wasted under no or partial participation. The corresponding prices for these three days are shown in Fig. 2.

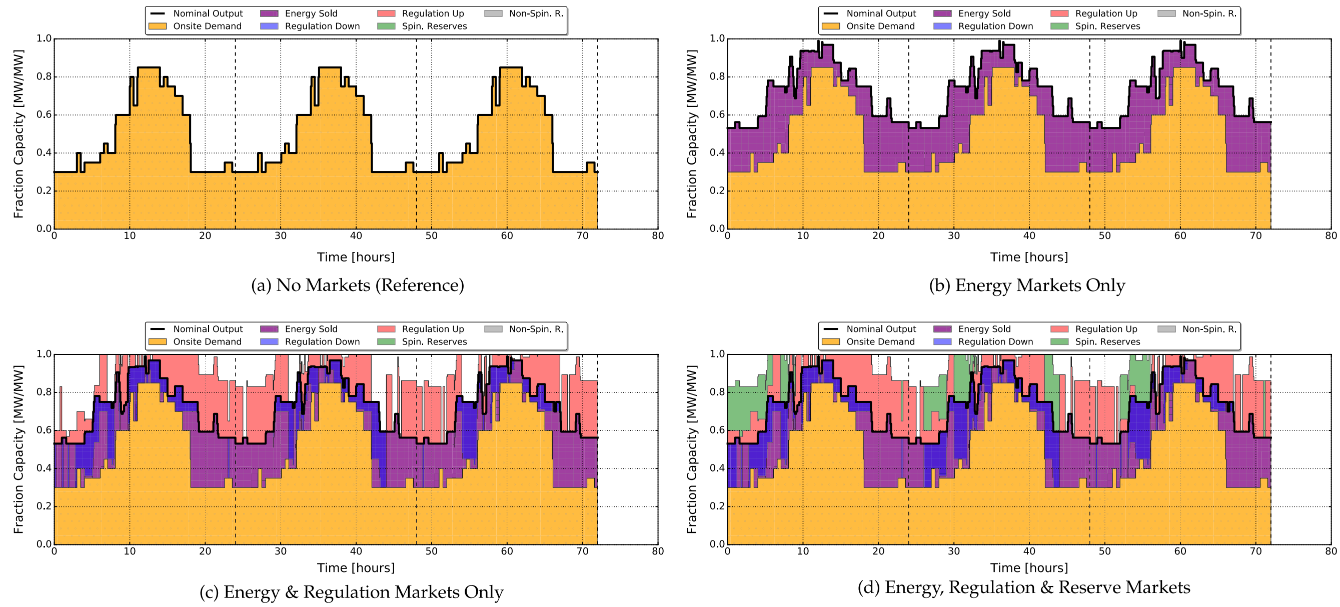
4.2. Revenues from different markets

The next study examines the distribution of revenues obtained from different timescales by comparing three market participation schemes: day-ahead (DAM) only, real-time (RTM) only, and full participation. Fig. 14 shows both the absolute fuel costs and revenues for combinations of market participation schemes and the four previously considered market schemes (i.e., combinations of products). Interestingly, with only energy sales in both DAM and RTM, approximately *one-third of the revenues comes from each timescale*. When ancillary services are considered, one-quarter of the revenues are from the 1-h (IFM) and 5-min (RTD) timescales, and the remaining half are from the 15-min timescale (FMM). When participation is restricted to the RTM only, one-half to two-thirds of the revenue come from the 15-min timescale (FMM). Table 2 shows the reduction in net operating costs for these combinations of market participation schemes and operating modes. The greatest savings are obtained by participating in markets at all timescales. Most notably, *restricting participation to only DAM limits cost savings to only 34–35% of those available from full market participation*. On the other hand, participating in only the RTM limits cost savings to 86–91% of the maximum available savings. Thus *the majority of the economic opportunities are obtained at faster timescales (5–15 min)*. Table 2 also shows that the cost savings for simultaneous ancillary services and energy participation are 228% higher than those obtained with energy participation (savings increase from 25,800 $/year to 57,900 $/year).

4.3. Benefits of demand flexibility

The previous results assume that onsite electricity and steam demands are completely inflexible (are followed exactly by the CHP system). Consequently, the CHP system can only use the residual capacity to participate in the markets. However, many industrial utility systems can provide three additional forms of flexibility: steam (represented by factor θ_s), electrical demands (θ_e), and additional regulation capacity (θ_r). The dominant time constants in many industrial unit operations (e.g., separation systems) are on the order of hours. As such, these systems may be insensitive to small steam supply fluctuations on the order of seconds or minutes. Headers in steam distribution systems also act as small storage volumes and can help attenuate high frequency variations. Both steam and electrical demand flexibility may also be available from adjustments in production schedules. Some loads for electrical headers and mechanical equipment (e.g., pumps, fans) may also be adjusted at high frequency to provide regulation

[2] For interpretation of color in 'Fig. 13', the reader is referred to the web version of this article.



(a) No Markets (Reference)

(b) Energy Markets Only

(c) Energy & Regulation Markets Only

(d) Energy, Regulation & Reserve Markets

Fig. 13. Comparison of operating policy for January 1–3, 2015 assuming 4.0 \$/MBtu fuel price.

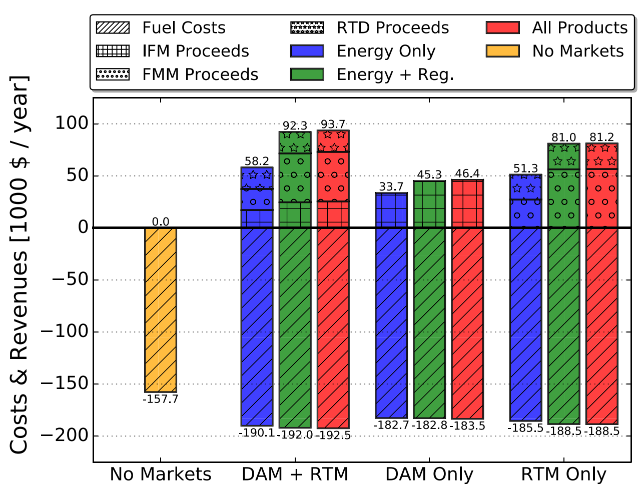


Fig. 14. Absolute fuel costs (negative) and revenues from markets, separated by market participation and product, assuming fuel price of 4.0 \$/MBtu.

services without compromising the performance of the other units at slower timescales.

These flexibility modes are investigated by individually varying θ_s, θ_e, and θ_r between 0% and 10% and resolving the operational optimization problem for different market interaction schemes. The total on-site daily steam and electricity demands are still satisfied (demand profiles are only shifted in time). For all three modes of flexibility, the relationship between net operating cost and flexibility parameter was found to be linear. The slopes signify the *value of flexibility*, and are reported in Table 3. *Market participation increases the value of flexibility by a factor of three to five* relative to no market participation. This *translates to additional costs savings of +1.4% to +3.5% by moving from 0% to 10% flexibility*.

The benefits of flexibility in CHP systems are derived from complex trade-offs between system efficiency and market opportunities. In particular *demand flexibility allows synchronization of on-site steam and electricity demands, which are often out of phase*. Without market participation, steam (θ_s) and electrical demand flexibility (θ_e) increase overall energy efficiency from 62.7% to 63.1–63.4%, as shown in Table 4. Increased energy efficiencies translate to fuel conservation and operating cost savings. In contrast, overall energy efficiency with market participation is approximately 2%-points lower. These trends are explained through Fig. 15, which are histograms showing the frequency of operation in the steam-electricity space. Even without market participation, exploiting steam demand flexibility allows the utility system to operate in more efficient regions (by synchronizing steam and electricity loads). With market participation, on the other hand, operation is shifted towards generating more electricity and exploiting excess capacity, even if this comes at the expense of less system efficiency (e.g., more fuel use). This is because, at the available CAISO market and fuel prices, selling additional energy outweighs less efficient operations. Increasing θ_s from 0% to 10% allows for more energy to be sold during higher prices. This has three consequences: (i) average energy selling price increases by

Table 2
Comparison of net operating cost savings for different market participation and operating mode combinations (relative to no market participation). Numbers in parenthesis show the net savings as a percentage of operating costs with no participation. The second line of each entry gives the fraction of available net savings relative to participation in all markets for each operating mode. This reveals the consequence of restricting market participation to either DAM or RTM timescales only.

	DAM + RTM	DAM only	RTM only
Energy only	25.8 k\$/year (16.3%) 100%	8.7 k\$/year (5.6%) 34 %	23.5 k\$/year (14.9%) 91%
Energy & regulation	57.9 k\$/year (36.7%) 100%	20.2 k\$/year (12.8%) 35 %	50.6 k\$/year (31.9%) 87%
All products	58.8 k\$/year (37.3%) 100%	20.7 k\$/year (13.1%) 35%	50.4 k\$/year (32.0%) 86%

Table 3
Value for different flexibility modes and different market participation schemes in thousands of dollars per % flexibility per year.

Flexibility mode	No markets	Energy only	All products
Steam (θ_s)	−0.135	−0.352	−0.346
Electrical (θ_e)	−0.133	−0.517	−0.628
Regulation (θ_r)	0	0	−0.225

Table 4
Impact of onsite demand flexibility on efficiency under market participation schemes.

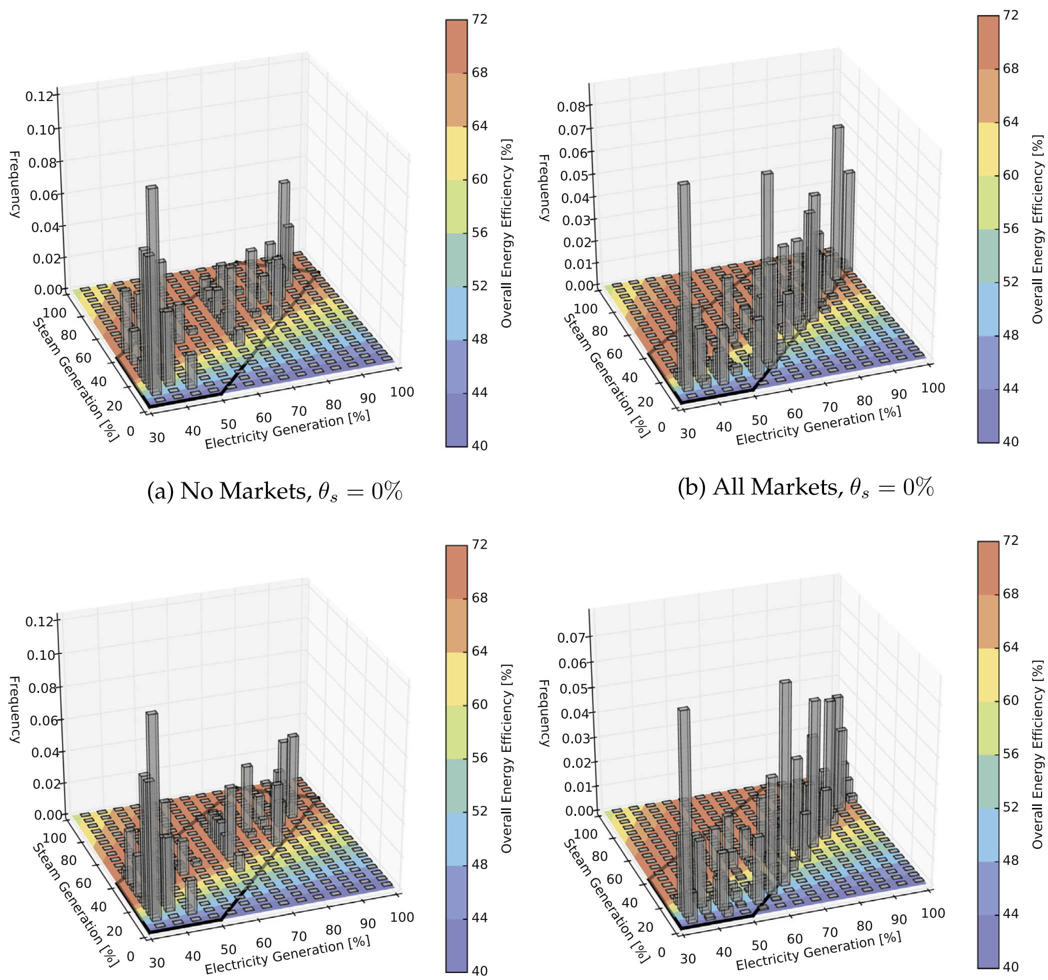
Market participation	$\theta_s = 0\%$ $\theta_e = 0\%$	$\theta_s = 10\%$ $\theta_e = 0\%$	$\theta_s = 0\%$ $\theta_e = 10\%$
None	62.7%	63.4%	63.1%
Energy only	60.1%	60.8%	60.2%
Energy & regulation	59.9%	60.6%	59.7%
All products	59.9%	60.6%	59.7%

2 \$/MW h, (ii) total energy sales decrease by 20–30 MW h (2–3%), and (iii) overall energy efficiency increases by 0.7%-points. Thus exploiting system flexibility and multi-scale markets provides significant economic incentives.

To further explore the trade-offs between steam and electricity generation, market prices and efficiency, a full flexibility case with $\theta_s = 100\%$ is considered. The delivered onsite steam and demand profiles as well as energy sales for three days are shown in Fig. 16. The six spikes in energy sales, located during hours (i) 0–9, (ii) 18–22, (iii) 27–33, (iv) 42–49, (v) 54–58, and (vi) 65–72, all correspond with periods of high energy prices (Fig. 2a). At these times, steam production is increased (relative to the reference case) to synchronize with increased electricity generation in order to operate in a higher efficiency region (Fig. 10). Similarly, during time periods with low energy prices little or no electricity is sold to the market and steam production is decreased. Fig. 16 indicates that a majority of energy is sold in the real-time time markets, which reflects the price trends see in Fig. 2a. From the steam and demand profiles it is clear that the system commands fast variations in steam capacity in order to exploit real-time market signals. Navigating these complex trade-offs between steam and electricity onsite demands, efficiency, and multi-scale price signals is virtually impossible without a systematic optimization framework.

4.4. CHP case study conclusions

This analysis reveals substantial opportunities for operating cost reductions (in the range of 16.3–59.1%) via market participation at all timescales. Interestingly, the *majority of these economic opportunities are provided by real-time markets*, which are neglected in most studies available in the literature. Exploiting onsite demand flexibility further improves savings, with electrical demand flexibility offering the greatest potential. All of these cost savings are realized through strategically manipulating the steam



(a) No Markets, $\theta_s = 0\%$

(b) All Markets, $\theta_s = 0\%$

(c) No Markets, $\theta_s = 10\%$

(d) All Markets, $\theta_s = 10\%$

Fig. 15. Distribution of operating points in steam-electricity generation space.

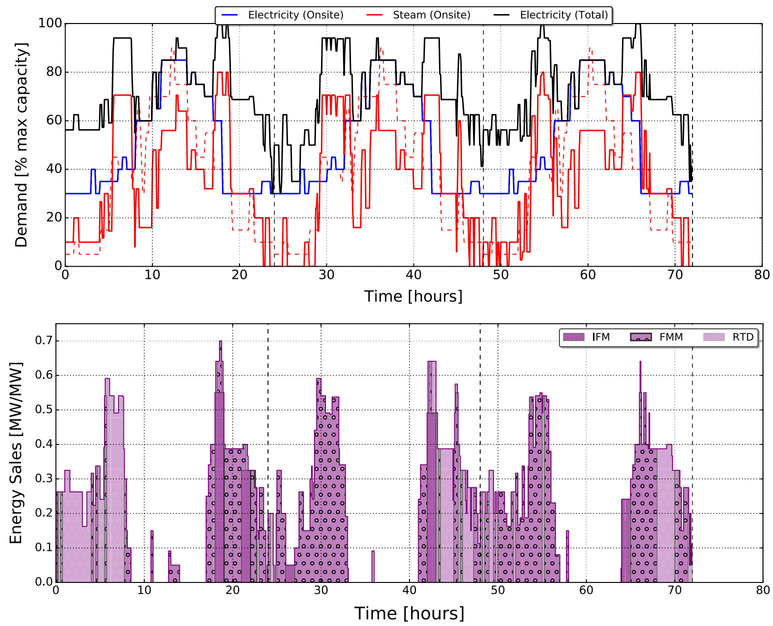


Fig. 16. (Top) Steam and electricity onsite demand profiles for January 1–3. The dashed line red lines show the reference steam demand. (Bottom) Sold power generation capacity (MW/MW, scaled by Λ^E) distinguished by market. The shaded (purple) area is energy (MW h/MW, scaled by Λ^E). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

and electricity production schedule in response to complex multi-layer energy and ancillary price signals and by operating under regions of higher efficiency.

5. Case study: battery storage system

The second case study considers the participation of a simple battery storage system in CAISO markets. The evolution of the battery state of charge (S) is modeled as follows:

$$S_{t_3^*(t)} = S_{t_3^*(t-1)} + \eta^+ \Delta t_3 \left(\sum_{\ell\in\mathcal{L}} \underline{E}_{t_\ell^*(t)}\right) - \frac{\Delta t_3}{\eta^-}\left(\hat{E}_{t_3^*(t)} + \sum_{\ell\in\mathcal{L}} \bar{E}_{t_\ell^*(t)}\right), \quad t \in \mathcal{T}^* \tag{5.41}$$

$$0 \leqslant S_{t_3^*(t)} \leqslant \bar{S}, \quad t \in \mathcal{T}^*, \tag{5.42}$$

where η^+ and η^- are the charge and discharge efficiencies, respectively, S_0 is the initial storage level and final storage level imposed at the end of each night, and $\bar{S}$ is the storage capacity. The following constraints are used to ensure sufficient storage capacity to accommodate regulation sales:

$$S_{t_3^*(t)} + \eta^+ \Delta t_3 \sum_{\ell\in\mathcal{L}} r^-_{t_\ell^*(t)} \leqslant \bar{S}, \quad t \in \mathcal{T}^*, \tag{5.43}$$

$$S_{t_3^*(t)} - \frac{\Delta t_3}{\eta^-} \sum_{\ell\in\mathcal{L}} r^+_{t_\ell^*(t)} \geqslant 0, \quad t \in \mathcal{T}^*. \tag{5.44}$$

Net market revenue is maximized by manipulating the amount of energy purchased, energy sold, and ancillary service capacity provided in the three CAISO market layers subject to the market model given by constraints (3.2)–(3.9) and (3.22)–(3.26), and the battery state of charge model given by (5.41)–(5.44). The parameter values $\eta^- = 95\%$, $\eta^+ = 95\%$, $\Lambda^E = 1$ MW (charge/discharge capacity), and $\bar{S} = 1$ MW h (energy storage capacity) are assumed.

Table 5 presents the revenue estimates for the battery system under different operating policy restrictions. Performing only energy arbitrage in all three market layers yields 139,100 $/year in net revenue. Adding ancillary services participation increases net revenues to 199,600 $/year (44% increase). Interestingly, restricting participation to only the day-ahead market (IFM) reduces net revenues substantially: 10,500 $/year (energy only) and 72,800 $/year (energy and ancillary services). Thus with only DAM participation, also providing ancillary services increases revenues by 600% relative to only energy arbitrage. These results also highlight the importance of studying revenues available at multiple market layers, especially at fast timescales. In particular, most previous studies for batteries only estimate revenues using day-ahead market prices [3,40,45,41,53,57], and thus miss important economic opportunities.

Table 6 examines the total energy transactions (sales and purchases) and average prices under six operating modes and market participation schemes. The difference between sale and purchase prices are greatest for the fastest market layers. For the RTD layer (5-min intervals, fastest timescale), the average price difference ranges from 39.5 to 53.2 $/MW h, whereas the average price difference for the IFM layer (1-h intervals, slowest timescale) ranges from 6.3 to 19.3 $/MW h. This is due to both lower purchase prices and higher sale prices at the faster timescales. Interestingly, with participation in multiple timescales, the dominant trend is to purchase energy in the RTD layer and resell it in the slower layers (IFM and FMM). A likely source of these opportunities is the slow dynamics of large thermal generators. For example, the RTD is used to settle deviations between instructed and actual electricity generation amounts from slower timescales due to physical ramping limitations. Because battery systems have much faster dynamics, they are capable of exploiting opportunities in the RTD (fastest market layer). In contrast, virtual bids are restricted to the IFM (day-ahead) and FMM (real-time) only (as required by CAISO market rules). As shown in Tables 5 and 6, strategic *virtual bidding (capped at 1 MW for consistency) produces seven times more revenue than performing energy arbitrage in the day-ahead market, but only 34–48% of the revenue available from participation in multiple market*

Table 5
Revenues for different market participation schemes and operating mode combinations (relative to no market participation). Percentages reflect the fraction of available revenue from participation in both the DAM and RTM.

	DAM + RTM	DAM only	RTM only
Energy only	139.1 k$/year 100%	10.5 k$/year 8 %	115.0 k$/year 83%
Energy & regulation	199.6 k$/year 100%	72.8 k$/year 36 %	141.8 k$/year 71%
All products	199.6 k$/year 100%	72.8 k$/year 36%	141.8 k$/year 71%
Virtual bidding		67.1 k$/year	

layers. Again, this is because virtual bids cannot exploit revenue opportunities in the faster market layer (RTD). This study thus highlights revenue opportunities for electricity storage systems from markets at faster timescales, and demonstrates the utility and general applicability of the proposed market participation model. Table 5 also shows that the revenues for simultaneous ancillary services and energy participation are 43% higher than those obtained with energy participation (revenue increases from 139,100 $/year to 199,600 $/year). This, again, illustrates how the proposed framework can be used to identify which market layers and products offer the greatest economic potential.

6. Conclusions and future work

This paper presents an optimization framework that captures transactions of different products and at different timescales between market participants and the independent system operator. We use real data from CAISO to analyze the interplay between dynamic flexibility (dictated by system physics and constraints) and market revenue potentials for CHP and battery energy storage systems. For both technologies, we find that a large fraction of revenue opportunities are provided by real-time markets (the fastest timescales). We also demonstrate that ancillary services markets in CAISO provide significant economic potential. Our results highlight that existing techno-economic studies that focus exclusively on day-ahead energy markets (operating at slower timescales) can dramatically undervalue dynamic flexibility. The findings of this paper prompt three areas of future work.

6.1. Uncertainty and real-time control

This paper assumes perfect information of energy prices and thus estimates the maximum available revenue opportunities from historical market data. In reality, energy system operators must consider risk from market prices and input "fuel availability" (natural gas availability under constrained distribution systems, solar or wind inputs for hybrid systems, etc.) when bidding into markets. Several studies previously classify the impact of forecasting error on market revenues [56,66,52]. Similarly, another group of studies proposes market participation strategies that explicitly consider risk for single timescale and/or single product contexts [57,62,67–70]. The key challenge is extending forecasting and robust market participation strategies to the full market participation context and characterizing the trade-offs between risk and revenue from different time-scales and products. Similarly, the proposed framework can be used as a basis for economic model predictive control strategies for systems participating in multi-scale energy markets.

6.2. Design of flexible energy systems

This paper demonstrates that current (year 2015) market data strongly incentivizes the design of energy systems with high dynamic flexibility (that can be monetized in the real-time market). As future work, we propose extending the framework to co-optimize market participation and design decisions (e.g., subsystem selection and sizing, etc.). Several recent studies, for instance, have focused on the design of flexible chemical manufacturing systems for operation under time-varying energy prices [23,71,25,27]. Our analysis informs these efforts by establishing an explicit link between dynamic flexibility at different timescale and revenue opportunities. Moreover, our framework can identify the critical physical constraints that limit revenue opportunities,

Table 6
Optimal energy sales and purchases for 1 MW (charge/discharge), 1 MW h (energy storage) battery operating in CAISO market for 2015. Average prices are reported for each timescale.

	Integrated forward market		Fifteen minute market		Real time dispatch	
	Sold	Purchased	Sold	Purchased	Sold	Purchased
Energy only						
DAM + RTM	3.16 GW h 34.3 $/MW h	1.17 GW h 26.6 $/MW h	1.94 GW h 44.3 $/MW h	1.80 GW h 20.3 $/MW h	1.22 GW h 71.9 $/MW h	4.03 GW h 18.7 $/MW h
DAM only	0.62 GW h 41.5 $/MW h	0.69 GW h 22.3 $/MW h	– –	– –	– –	– –
RTM only	– –	– –	2.74 GW h 38.2 $/MW h	1.43 GW h 19.0 $/MW h	1.45 GW h 63.2 $/MW h	3.22 GW h 16.9 $/MW h
All products						
DAM + RTM	2.86 GW h 33.5 $/MW h	1.18 GW h 27.2 $/MW h	1.81 GW h 38.9 $/MW h	1.66 GW h 21.1 $/MW h	1.27 GW h 67.1 $/MW h	3.75 GW h 19.1 $/MW h
DAM only	0.55 GW h 39.0 $/MW h	0.61 GW h 24.5 $/MW h	– –	– –	– –	– –
RTM only	– –	– –	2.64 GW h 34.3 $/MW h	1.47 GW h 21.8 $/MW h	1.60 GW h 58.1 $/MW h	3.23 GW h 18.6 $/MW h
Virtual bidding	5.2 GW h 32.4 $/MW h	3.5 GW h 29.6 $/MW h	3.5 GW h 37.2 $/MW h	5.2 GW h 24.6 $/MW h	– –	– –

providing a systematic methodology to design flexible manufacturing systems.

6.3. Energy infrastructures and public policy

The proposed framework offers a data-analytics tool to uncover the economic incentives embedded in market price data. This can help policy-makers understand if current markets are meeting policy goals (e.g., renewable adoption). With additional infrastructure models, the proposed framework can analyze new renewable integration, coupled infrastructures (e.g., natural gas and electricity markets), or new market rules from the context of investors/system owners [72,73]. Moreover, the framework offers alternate metrics besides the *defacto* standard, levelized cost of electricity (which ignores all time-varying effects), to more holistically compare energy technologies and guide research investments [74,75].

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Appendix A. Nomenclature

A.1. Parameters

Symbol	*Description*	*Units*
Δt_ℓ	Timestep at level ℓ	[h]
ϵ	Small number (10^{-6})	[–]
$\pi^A_{a,t^*_\ell(t)}$	Price for ancillary service $a \in \mathcal{A}$ at level $l \in \mathcal{L}$	\$/(MW × [h])
$\pi^E_{t^*_\ell(t)}$	Price for energy at level $l \in \mathcal{L}$	\$/(MW × [h])
ρ^{max}_{reg}	Maximum total regulation	[–]*
ρ^{max}_{+}	Maximum up regulation	[–]*
ρ^{max}_{-}	Maximum down regulation	[–]*
ρ^E	Maximum ramp rate for electricity	1*/[h]
ρ^{steam}	Maximum ramp rate for steam	1†/[h]
Λ	Minimum operation capacity (electricity generation)	MW/MW
Λ^E	Nameplate electricity generation capacity	MW
Λ^{steam}	Nameplate steam generation capacity	MW
η^+	Battery charge efficiency	[–]
η^-	Battery discharge efficiency	[–]
η^{total}	Maximum overall utility (CHP) system efficiency	[–]
η^E	Maximum fuel to electrical energy efficiency	[–]
η^{steam}	Maximum fuel to steam energy efficiency	[–]
$\phi_{t^*_3(t)}$	Electricity demand at time $t \in \mathcal{T}^*$	[–]*
$\sigma_{t^*_3(t)}$	Steam demand at time $t \in \mathcal{T}^*$	[–]†
$\overline{S}$	Maximum battery capacity	[–]*
θ_e	Flexibility fraction for onsite electrical demand	[–]
θ_r	Fraction of onsite electrical demand that may be used for reg.	[–]
θ_s	Flexibility fraction for onsite steam demand	[–]

A.2. Sets

Set	*Description*
$\mathcal{A} := \{s, n, r^+, r^-\}$	Ancillary Services
$\mathcal{L} := \{3, 2, 1, 0\}$	Market layers
$\mathcal{T}_\ell := \{1, \ldots, N_\ell\}$	Set of time steps in timescale ℓ
$\mathcal{T}^*_\ell$	Nested time for timescales ℓ through 0 (days)

A.3. Variables

Variable	*Description*	*Units*
$A_{t^*_\ell(t)}$	Ancillary service quantity at level $\ell \in \mathcal{L}$	[–]*
$\bar{E}_{t^*_\ell(t)}$	Energy **sold** in market at level $\ell \in \mathcal{L}$	[–]*
$\underline{E}_{t^*_\ell(t)}$	Energy **purchased** in market at level $\ell \in \mathcal{L}$	[–]*
$E_{t^*_3(t)}$	Net energy **generated** at time $t \in \mathcal{T}^*$	[–]*
$\hat{E}_{t^*_3(t)}$	Electricity delivered to onsite demand at time $t \in \mathcal{T}^*$	[–]*
$f_{t^*_3(t)}$	Fuel consumption at time $t \in \mathcal{T}^*$	MW
$n_{t^*_\ell(t)}$	Non-spinning reserve capacity sold in market $\ell \in \mathcal{L}$	[–]*
$s_{t^*_\ell(t)}$	Spinning reserve capacity sold in market $\ell \in \mathcal{L}$	[–]*
$S_{t^*_3(t)}$	Battery storage level at time $t \in \mathcal{T}^*$	[–]*
S_0	Battery storage level at time $t = 0$ (initial condition)	[–]*
$\hat{s}_{t^*_3(t)}$	Steam delivered to onsite demand at time $t \in \mathcal{T}^*$	[–]†
$r^+_{t^*_\ell(t)}$	Regulation up capacity sold in market $\ell \in \mathcal{L}$	[–]*
$r^-_{t^*_\ell(t)}$	Regulation down capacity sold in market $\ell \in \mathcal{L}$	[–]*
$R_{t^*_3(t)}$	Regulation capacity covered by energy sales	[–]*
R_A	Revenue from ancillary service sales	\$
R_E	Net revenue from energy sales/purchases	\$
$z_{t^*_3(t)}$	Intermediate variable for ramp rate constraint	[–]*

† These variables and parameters are scaled by steam generation nameplate capacity, Λ^{steam}.

* These variables and parameters are scaled by the electricity generation nameplate capacity, Λ^E.

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