Double-Signal Retail Pricing Scheme for Acquiring Operational Flexibility From Batteries

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***Abstract*—Batteries can provide valuable operational flexibility to facilitate the system efficiency. However, there lacks market environments to effectively harness and monetize the value of these assets. Most existing works apply a profit-oriented single-signal pricing scheme, which mixes the value of energy and flexibility together and may ultimately raise the electricity bills. Therefore, this paper proposes a profit-neutral double-signal retail pricing scheme that distinguishes elastic market players (i.e., batteries) from inelastic market players (i.e., inflexible loads) and quantifies the value of energy and flexibility separately. Experimental results indicate that under the incentive provided by the proposed retail pricing scheme: 1) The system efficiency benefit aligns with benefits to both batteries and inflexible loads; 2) Value of operational flexibility, contributing to improve the energy efficiency, can be transparently priced and fairly allocated among batteries; and 3) The dominant role in which inflexible loads play on determining the market price is avoided.**

***Index Terms*—Battery arbitrage, bi-level optimization, price-responsive behavior, retail pricing.**

Nomenclature

α^t	Wholesale price ($\$/kWh$) at hour t
β^t	Retail price ($\$/kWh$) at hour t under the single-signal pricing scheme
β_E^t	Retail energy price ($\$/kWh$) at hour t
β_{GS}^t	Retail grid service price ($\$/kWh$) at hour t
δ_{sub}	Subsidy rate (%)
$\mathcal{N}_E$	The set of elastic participants
$\mathcal{N}_I$	The set of inelastic participants
C_β	Sum of the retail grid service prices over 24-hour
C_j	Capacity (kWh) of the jth battery
$D_{kWh,j}$	Degradation rate ($\$/kWh$) of the jth battery
$l_{c,j}$	Charging loss ratio (%) of the jth battery
$l_{d,j}$	Discharging loss ratio (%) of the jth battery
$P_{in,j}^t$	Energy (kWh) purchased from the retail market by the jth elastic participant at hour t
$P_{L,i}^t$	Inflexible load (kWh) owned by the ith inelastic participant at hour t
$P_{out,j}^t$	Energy (kWh) sold to the retail market by the jth elastic participant at hour t
P_S^t	Energy (kWh) injected from the substation at hour t
R_j^{max}	Maximum dis-/charging rate (kW) of the jth battery
R_j^t	Dis-/charging rate (kW) of the jth battery at hour t
$s_{GS,j}$	Grid service subsidy for the jth elastic participant
S_{GS}	Total grid service subsidy
SoC_j^{end}	Minimum state of charge (%) of the jth battery to be maintained at the end of the operating day
SoC_j^{init}	Initial state of charge (%) of the jth battery
SoC_j^{max}	Maximum state of charge (%) of the jth battery
SoC_j^{min}	Minimum state of charge (%) of the jth battery
SoC_j^t	State of charge (%) of the jth battery at hour t

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I. Introduction

The emergence of the distributed energy resource (DER) technology is now reshaping the modern power industry, bringing benefits like low marginal cost, low transmission loss and high operational flexibility. Federal Energy Regulatory Commission Order 2222 [1] opens the wholesale market for DERs to compete with traditional resources in providing grid services required for system balancing, efficiency and reliability. On the retail market side, efforts have also been made on engaging DERs via offering the net metering [2] or demand response (DR) programs [3], [4].

Despite the encouraging message from government and industry as well as the growing share of electricity supply from DERs [5], nowadays DERs are principally installed behind-the-meter and used to meet onsite demands. Their participation is generally limited to DR programs. Apart from the technological and regulatory burdens [6], two major economic deficiencies drive this low participation rate: 1) There lacks effective pricing schemes to properly incent and coordinate the behaviors of DERs while ensuring the collective and individual revenue adequacy of DERs; 2) Financial compensations paid to DERs, determined by the market tariff, are not in alignment with their real contributions to the system efficiency. This paper, therefore, seeks to address these two deficiencies at the retail level to accelerate the integration of batteries, as a popular type of DERs with inter-temporal operational flexibility.

Net-metering and DR programs play important roles in enhancing the energy efficiency, however, are not designed to maximize the value of DERs. They utilize the resources either locally or within a limited time window. The flexibility to adjust consumption/generation during the DR window is compensated by a fixed amount of financial incentive, which does not reflect its real value to the energy efficiency. As the operational flexibility of batteries is fundamentally driven by the temporal price difference, a dynamic retail price that varies over short time intervals reflecting the fluctuation of system operating status serves as the greatest incentive [7].

During the last decade, increasing attention has been devoted to retail dynamic pricing for various types of DERs. Samadi *et al.* [8] developed a real-time pricing tool for efficient demand side management. A distributed generation (DG) acquisition model was proposed in [9] that determines the optimal contract price of DGs to minimize the energy procurement cost. Fuller *et al.* proposed a transactive energy market in [10] based on double auction considering flexibility offered from both demand and generation sides. Asimakopoulou *et al.* [11] formulated a competitive market between a centralized production unit and energy service providers, who manage over both controllable loads and distributed generators. Maharjan *et al.* [12] extended the discussion to a market with multiple retailers and customers where retailers compete with each other through optimizing their own pricing strategies. A common issue of aforementioned papers is that they are only applicable for the spot market and have ignored the opportunity cost (i.e., the gain of the asset from not running during a particular interval but saving stored energy for an interval with higher price) associated with DERs, as the flexibility is defined as the price elasticity of demand/generation in a single period. However, batteries are with strict inter-temporal operational constraints due to the limited energy storage, whose opportunity costs cannot be ignored. In addition, concerns have been raised in [13] and [14] that DERs' price-responsive behaviors result in additional price volatility in the spot market, since their reactions to the current price influences the price in the upcoming period [15]. To hedge the spot price volatility and respect the inter-temporal constraints of DERs, it is critical to have a short-term forward market that plans multi-period operations of DERs ahead of the spot market.

Studies have also been conducted to address the above need. Doostizadeh *et al.* [16] developed a day-ahead pricing model to manage the price-elastic loads. An across-elasticity component is added to the utility function to model the sensitivity of demand towards the price difference among timestamps. More commonly, the bi-level optimization framework is applied to formulate the multi-period retail pricing problem in the literature, with the lower-level problem models the price sensitivity of DERs and the upper-level problem determines the price. Day-ahead retail pricing schemes for managing price-sensitive electric heating storage and load serving entities were introduced in [17] and [18]. Wei *et al.* in [19] proposed a two-level two-stage day-ahead retail pricing scheme by considering the uncertain variance between day-ahead and real-time prices. A stochastic bi-level optimization framework was invented in [20] to handle multiple sources of uncertainties in the market. Despite the extensive discussion on the topic of retail forward pricing, three knowledge gaps have been identified: Firstly, all aforementioned studies assume the retail market operator (RMO) to be profit-oriented. Such a design tends to benefit the RMO in exchange of sacrificing the system efficiency and inflexible customers by raising the market price as much as possible during the peak load hours; Secondly, market participants, whether can or cannot provide the operational flexibility, are charged/credited at the same price. This single-signal scheme, however, forces the market price to be dominantly influenced by the type of market participants summing up to a larger capacity. Also, we think the flexibility and energy products are essentially distinct and should be valued separately by two transparent pricing signals; Finally, how the price signal can be used to reflect the real value of DERs in improving the energy efficiency is not discussed.

Given the aforementioned knowledge gaps, we propose a profit-neutral double-signal day-ahead retail pricing scheme in this study with following contributions being made:

1) To the best of our knowledge, this paper introduces a profit-neutral double-signal retail pricing scheme and compares it with other three alternatives (i.e., profit-neutral & single-signal, profit-oriented & single-signal and profit-oriented & double-signal) for the first time.
2) A retail grid service price is introduced, in addition to the retail energy price, to separately quantify and fairly allocate the value of flexibility provided by individual private-owned battery in reducing the overall system cost.
3) A retail grid subsidy is introduced to provide supplementary incentive to the batteries. It helps further improve the participation rate of batteries and ultimately secures the benefits for both batteries and non-flexible loads.

The remainder of the paper is organized as follows: Section II outlines the proposed retail market model. Section III specifies the retail pricing problem formulation using a bi-level optimization framework. The bi-level problem is converted into a mixed integer linear programming (MILP) problem in Section IV. Case studies are demonstrated in Section V. Finally, Section VI concludes the paper and proposes future work.

II. The Proposed Market Model

A tri-layer (wholesale-retail-players) market model, presented in Fig. 1, provides the market context in the study. The RMO acts as an intermediary agent between the wholesale market at the top layer and market participants at the bottom layer, and interacts with them through energy and financial transactions. Two types of dispatchable energy resources are present in the market: i) the supply from the bulk grid accessible at the substation, which can be purchased at the wholesale price; and ii) the operational flexibility provided by batteries accessible at distributed locations, which can be purchased at the retail price. Several assumptions are made on the market model:

1) The RMO is profit-neutral. In other words, its decisions are not driven to maximize the gap between the revenue

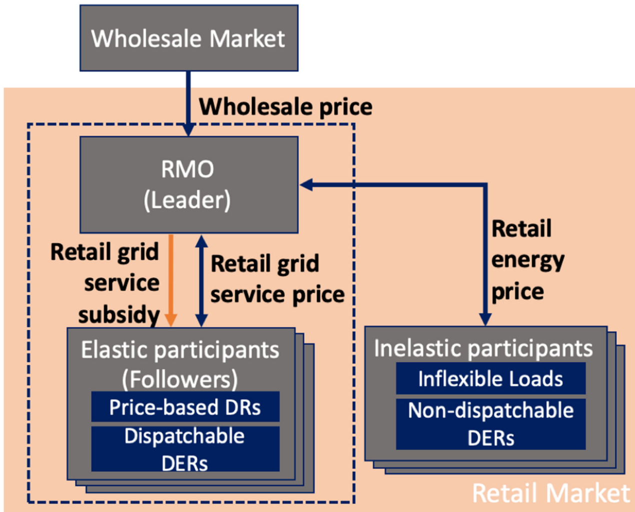


Fig. 1. The proposed market model.

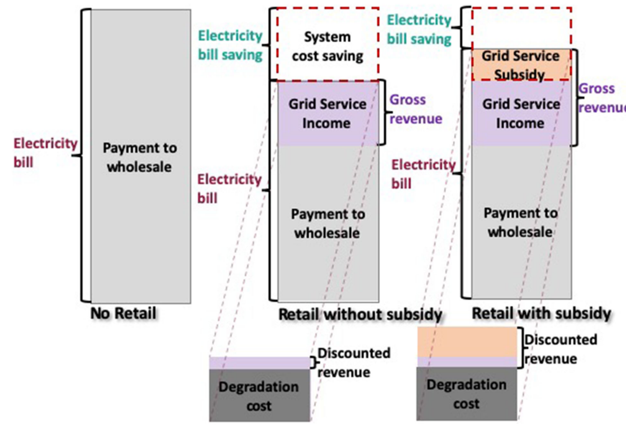


Fig. 2. Illustration of three types of market settlements: No retail, retail without subsidy and retail with subsidy.

earned from customers' electricity bills and the cost paid to generating units, but to improve the system efficiency.

2) All batteries are private-owned. The RMO does not have the authority to directly control them, unlike utility-owned batteries, but can incentivize their operations through the pricing tool.
3) The RMO is assumed to be a price-taker in the wholesale market in order to put the emphasis on interactions within the retail market.
4) The RMO has the full knowledge of key parameters and initial operating statuses of batteries, which are necessary for understanding their price-responsive behaviors.

Without loss of generality, we classify the market players into two groups: *inelastic participants* and *elastic participants* based on their sensitivity to the market price. In other words, application of the proposed retail market model is not limited to the market with only inflexible loads (i.e., a representative type of inelastic participants) and batteries (i.e., a representative type of elastic participants) as what is investigated in this study. Accordingly, a double-signal pricing scheme consisting of a retail energy price signal ($\boldsymbol{\beta_E} = [\beta_E^1, \beta_E^2, \ldots, \beta_E^{24}]^\top$) and a retail grid service price signal ($\boldsymbol{\beta_{GS}} = [\beta_{GS}^1, \beta_{GS}^2, \ldots, \beta_{GS}^{24}]^\top$) is proposed. Inelastic participants are charged/credited at the retail energy price and their behaviors are insensitive to the price. Typical examples include inflexible loads and non-dispatchable DERs. Elastic participants are charged/credited at the retail grid service price and their behaviors are sensitive to the price. Typical examples include price-based DRs and dispatchable DERs. Due to the costly degradation effect of batteries or other types of DERs, e.g., heat pump, a retail grid service subsidy is introduced to further motivate the participation of elastic participants. As shown in Fig. 2, the subsidy is basically a share of benefit being transferred from inelastic participants (in terms of electricity bill saving) to elastic participants (in terms of revenue). A subsidy rate δ_{sub} defines the proportion of the grid service subsidy out of the system cost saving, and controls the trade-off between benefits shared to inelastic and elastic participants. Detailed subsidy settlement and allocation among elastic participants are discussed in Section III-B.

The dashed line in Fig. 1 frames two types of decision-makers in the retail market. They make decisions in sequence, following a leader-followers game. The RMO acts first as the leader and optimizes the retail grid service price to minimize the overall system cost. After the retail grid service price is announced, elastic participants then, acting as followers, plan next-day operations to maximize their payoffs/profits from the retail market. Since profits earned by elastic participants are a part of the system cost, how elastic participants react to the retail grid service price in turn affects effectiveness of RMO's decisions. The closer the RMO is able to capture the price-responsive behaviors of elastic participants, the more effective the rendered market price will be. Such a correlated decision-making process turns the retail pricing problem into a bi-level optimization problem, with a upper-level system resources scheduling problem and multiple lower-level payoff optimization problems. Since batteries are the only type of elastic participants in this study, the lower-level problems become battery arbitrage problems.

III. Double-Signal Pricing Scheme

Detailed formulation of the double-signal retail pricing problem is provided in this section based on the market model outlined above.

A. Lower-Level Battery Arbitrage Problem

The arbitrage behavior of a single battery (indexed by j) in response to β_{GS}^t is stated in (1) [21]. It aims at maximizing the discounted profit of the battery in a 24-hour control horizon (one-hour control resolution) while taking equipment physical dynamics and battery degradation into account.

$$\underset{\substack{\boldsymbol{P_{in,j}},\boldsymbol{P_{out,j}}\\ \boldsymbol{SoC_j},\boldsymbol{R_j}}}{\textbf{maximize}} \ \sum_{t=1}^{24} \beta_{GS}^t \left(P_{out,j}^t - P_{in,j}^t\right) - \sum_{t=1}^{24} D_{kWh,j} R_j^t$$

$$\textbf{subject to} \tag{1a}$$

$$SoC_j^1 = SoC_j^{init} + \frac{P_{in,j}^1 \left(1 - l_{c,j}\right)}{C_j} - \frac{P_{out,j}^1}{\left(1 - l_{d,j}\right) C_j} \leftrightarrow u_{soc,j}^1 \tag{1b}$$

$$SoC_j^t = SoC_j^{t-1} + \frac{P_{in,j}^t \left(1 - l_{c,j}\right)}{C_j} - \frac{P_{out,j}^t}{\left(1 - l_{d,j}\right) C_j} \leftrightarrow u_{soc,j}^t, \quad t \in [2, 24] \tag{1c}$$

$$R_j^t = P_{in,j}^t \left(1 - l_{c,j}\right) + \frac{P_{out,j}^t}{1 - l_{d,j}} \leftrightarrow u_{R,j}^t, \forall t \tag{1d}$$

$$SoC_j^{\min} \leq SoC_j^t \leq SoC_j^{\max} \leftrightarrow \underline{v_{\text{soc},j}^t}\overline{v_{\text{soc},j}^t}, t \in [1, 23] \tag{1e}$$

$$SoC_j^{end} \leq SoC_j^{24} \leq SoC_j^{max} \leftrightarrow \underline{v_{soc,j}^{24}}, \overline{v_{soc,j}^{24}} \tag{1f}$$

$$0 \leq R_j^t \leq R_j^{\max} \leftrightarrow \underline{v_{R,j}^t}, \overline{v_{R,j}^t}, \forall t \tag{1g}$$

$$P_{in,j}^t \geq 0 \leftrightarrow \underline{v_{P_{in,j}}^t}, \forall t \tag{1h}$$

$$P_{out,j}^t \geq 0 \leftrightarrow \underline{v_{P_{out,j}}^t}, \forall t \tag{1i}$$

$$P_{in,j}^t P_{out,j}^t = 0 \leftrightarrow u_{P,j}^t, \forall t \tag{1j}$$

Note that boldface letters indicate vectors or matrices, otherwise, scalars. Control variables are separately created for charging, $\boldsymbol{P_{in,j}} = [P_{in,j}^1, P_{in,j}^2, \ldots, P_{in,j}^{24}]^\top \in \mathbb{R}^{24}$, and discharging, $\boldsymbol{P_{out,j}} = [P_{out,j}^1, P_{out,j}^2, \ldots, P_{out,j}^{24}]^\top \in \mathbb{R}^{24}$, actions given that battery's charging and discharging loss ratios, $l_{c,j}$ and $l_{d,j}$, are generally unequal. $\boldsymbol{SoC_j} = [SoC_j^1, SoC_j^2, \ldots, SoC_j^{24}]^\top \in \mathbb{R}^{24}$ and $\boldsymbol{R_j} = [R_j^1, R_j^2, \ldots, R_j^{24}]^\top \in \mathbb{R}^{24}$ are state variables of the battery, representing the state of charge and dis-/charging rate at each hour. They can be sufficiently determined by the initial battery status and sequential controls, $\boldsymbol{P_{in,j}}$ and $\boldsymbol{P_{out,j}}$. Variables on the right hand side of "$\leftrightarrow$" indicate dual variables associated with each constraint. The objective function (1a) maximizes the net arbitrage income of the battery owner, and it is calculated by subtracting the daily degradation cost from the daily battery arbitrage revenue. Battery degradation is considered given its impact on the long-term battery profit and is approximately quantified as linearly related with the accumulated charging/discharging amounts. (1b) and (1c) describe dynamics of the SoC. (1d) computes the dis-/charging rate at each hour. Inequality constraints (1e)-(1g) bound the range of SoC_j^t and R_j^t. (1h) and (1i) enforce the sign of both charging and discharging control variables to be non-negative. Finally, (1j) avoids simultaneous charging and discharging behavior of the battery. In Appendix B, we prove that the omission of (1j) does not affect the optimal solution of (1) as long as the grid service price β_{GS}^t is strictly non-negative. It is proven given that any solution with simultaneous charging and discharging operation ($P_{in,j}^t > 0$ & $P_{out,j}^t > 0$ for any t) is suboptimal.

B. Upper-Level System Resources Scheduling Problem

According to Section II, the upper-level problem is essentially a day-ahead system resources scheduling problem with RMO being the decision maker. It seeks to meet the demand of inelastic participants at a minimum cost by optimizing the grid service price signal, $\boldsymbol{\beta_{GS}} = [\beta_{GS}^1, \beta_{GS}^2, \ldots, \beta_{GS}^{24}]^\top \in \mathbb{R}^{24}$. Such a decision making process can be mathematically expressed as what follows:

$$\underset{\boldsymbol{\beta_{GS}}, \boldsymbol{P_{out}}, \boldsymbol{P_{in}}}{\textbf{minimize}} \quad \sum_{t=1}^{24} \alpha^t P_S^t + \sum_{t=1}^{24} \sum_{j \in \mathcal{N}_E} \beta_{GS}^t \left(P_{out,j}^t - P_{in,j}^t\right)$$

$$\textbf{subject to} \tag{2a}$$

$$P_S^t + \sum_{j \in \mathcal{N}_E} \left(P_{out,j}^t - P_{in,j}^t\right) = \sum_{i \in \mathcal{N}_I} P_{L,i}^t, \forall t \tag{2b}$$

$$\boldsymbol{P_{out,j}}, \boldsymbol{P_{in,j}} := \underset{\boldsymbol{X_j}}{argmax}\{f_j(\boldsymbol{X_j}, \boldsymbol{\beta_{GS}}) : g_j(\boldsymbol{X_j}) \leq 0, h_j(\boldsymbol{X_j}) = 0\}, j \in \mathcal{N}_E \tag{2c}$$

$$\sum_{t=1}^{24} \beta_{GS}^t = C_\beta \tag{2d}$$

$$\beta_{GS}^t \geq 0, \forall t \tag{2e}$$

Where i and j index the inelastic and elastic participants in $\mathcal{N}_I$ and $\mathcal{N}_E$. $\boldsymbol{P_{out}} \in \mathbb{R}^{24 \times |\mathcal{N}_E|}$ and $\boldsymbol{P_{in}} \in \mathbb{R}^{24 \times |\mathcal{N}_E|}$)[1] are matrices assembling the $\boldsymbol{P_{out,j}}$ and $\boldsymbol{P_{in,j}}$ decision variables from all $|\mathcal{N}_E|$ lower-level problems. $\boldsymbol{X_j}$, $f_j(\cdot)$, $g_j(\cdot)$ and $h_j(\cdot)$ represent the decision variables, objective function, i.e., (1a), inequality constraints, i.e., (1e)-(1i), and equality constraints, i.e., (1b)-(1d) and (1j), of the j^{th} lower-level problem. The objective function (2a) minimizes the total cost for serving the system inelastic demand over the 24-hour period, which consists of two parts: the cost paid to the wholesale market and the cost paid to battery owners. The system demand and supply balance is enforced by the equality constraint (2b). (2d) governs the average level of the retail grid service price signal. In practice, it is recommended to select C_β at a value that equals to the daily sum of grid energy prices $\boldsymbol{\beta_E}$ calculated based on historical data, such that retail grid service price and retail energy price are at similar order of magnitude on average. Constraint (2e) is added to support the linearization of lower-level problem (1) as analyzed in Section III-A and Appendix B. The mathematical relations between the upper-level decision variable (i.e., $\boldsymbol{\beta_{GS}}$) and lower-level decision variables (i.e., $\boldsymbol{P_{out,j}}$ and $\boldsymbol{P_{in,j}}$) from each lower-level problem are captured by (2c). It specifies that $\boldsymbol{P_{out,j}}$ and $\boldsymbol{P_{in,j}}$ are arguments that yield the maximum value of all lower-level problems. Such an implicit equation will be altered by an explicit replacement in Section IV to merge the two levels.

[1]Operator $|\cdot|$ indicates cardinality if applied on a set.

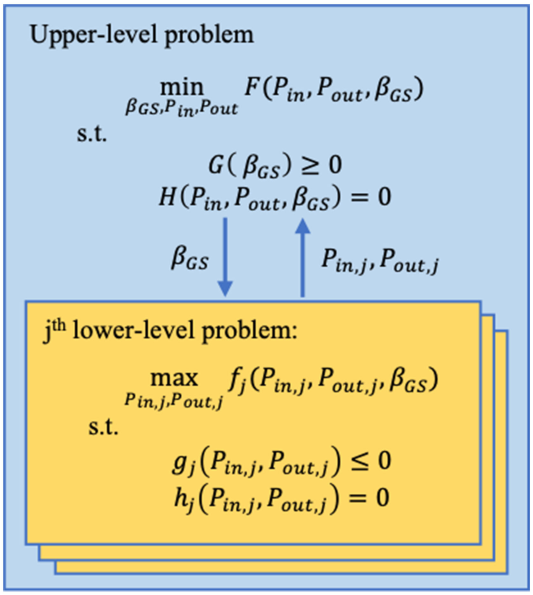


Fig. 3. The relation between upper and lower level problems.

C. Relation Between Upper-Level and Lower-Level Problems

Given the problem formulations outlined in Sections III-A and III-B, upper- and lower-level problems are highly coupled. To be more specific, lower-level problems are embedded in the upper-level problem as constraints. The upper-level decision variable, $\boldsymbol{\beta_{GS}}$, is an important parameter of the lower-level problems. Lower-level decision variables, $\boldsymbol{P_{out,j}}$ and $\boldsymbol{P_{in,j}}$, are also shared in the upper-level problem as intermediate decision variables, as illustrated in Fig. 3, in which $F(\cdot)$, $G(\cdot)$ and $H(\cdot)$ represent the objective function, i.e., (2a), inequality constraints, i.e., (2e), and equality constraints, i.e., (2b) and (2d), of the upper-level problem.

D. Market Settlement

Once the optimal solution, $\beta_{GS}^{t,*}$, $P_{out,j}^{t,*}$, and $P_{in,j}^{t,*}$, of the bi-level problem is obtained, optimal retail energy price, $\beta_E^{t,*}$, total grid service subsidy, S_{GS}^*, and the subsidy for individual battery, $s_{GS,j}^*$, can be uniquely determined based on the pre-defined subsidy rate δ_{sub}:

$$\beta_{AC}^{t,*} = \frac{\alpha^t P_S^t + \sum_{j\in\mathcal{N}_E}\beta_{GS}^{t,*}(P_{out,j}^{t,*} - P_{in,j}^{t,*})}{\sum_{i\in\mathcal{N}_I} P_{L,i}^t} \tag{3}$$

$$\beta_E^{t,*} = \delta_{sub}\alpha^t + (1-\delta_{sub})\beta_{AC}^{t,*} \tag{4}$$

$$S_{GS}^* = \delta_{sub}\sum_{t=1}^{24}\Bigg[\alpha^t\sum_{i\in\mathcal{N}_I}P_{L,i}^t - \alpha^t P_S^t - \beta_{GS}^{t,*}\sum_{j\in\mathcal{N}_E}(P_{out,j}^{t,*} - P_{in,j}^{t,*})\Bigg] \tag{5}$$

$$s_{GS,j}^* = \frac{\sum_{t=1}^{24}\beta_{GS}^{t,*}(P_{out,j}^{t,*} - P_{in,j}^{t,*})}{\sum_{j\in\mathcal{N}_E}\sum_{t=1}^{24}\beta_{GS}^{t,*}(P_{out,j}^{t,*} - P_{in,j}^{t,*})} S_{GS}^* \tag{6}$$

Where $\beta_{AC}^{t,*}$ represents the unit generation cost averaged over the system demand, $\sum_{i\in\mathcal{N}_I} P_{L,i}^t$, at time t. $\beta_E^{t,*}$ is weighted between α^t and $\beta_{AC}^{t,*}$ based on the subsidy rate, δ_{sub}, in (4). The total grid service subsidy, S_{GS}^*, equals δ_{sub} times the total generation cost saving (compared to the case when inelastic participants are charged at the wholesale price) in (5). And it is distributed among batteries based on their contributions made on improving the system efficiency, as shown in (6). Such a contribution can be quantified based on the grid service value monetized by the grid service price, $\beta_{GS}^{t,*}$. The subsidy to each battery is therefore proportional to the grid service value, $\sum_{t=1}^{24}\beta_{GS}^{t,*}(P_{out,j}^{t,*} - P_{in,j}^{t,*})$, it provides out of the total amount, $\sum_{j\in\mathcal{N}_E}\sum_{t=1}^{24}\beta_{GS}^{t,*}(P_{out,j}^{t,*} - P_{in,j}^{t,*})$. Note that the linear relation between α^t and β_E^t defined in (4) may expose the risk of wholesale price volatility to the retail market. To address this issue, in practice, the RMO could consider averaging out the energy price, β_E^t, over time or placing a price cap on it.

IV. Problem Reformulation

So far the upper-level and lower-level problems discussed in Section III are formulated independently, and thus cannot be solved directly. It calls for a reformulation of the original retail pricing problem, including coupling of two levels as well as linearization of cross-product terms.

A. Transformation of the Bi-Level Problem

KKT conditions of the lower-level problems are employed to couple the upper-level and lower-level problems, as they provide an explicit replacement of (2c). KKT conditions associated with the jth battery include four parts:

Stationarity:

$$-\beta_{GS}^t - \frac{u_{soc,j}^t}{(1-l_{d,j})\,C_j} + \frac{u_{R,j}^t}{1-l_{d,j}} - \underline{v}_{P_{out,j}}^t = 0, \forall t \tag{7a}$$

$$\beta_{GS}^t + \frac{u_{soc,j}^t\,(1-l_{c,j})}{C_j} + u_{R,j}^t\,(1-l_{c,j}) - \underline{v}_{P_{in,j}}^t = 0, \forall t \tag{7b}$$

$$u_{soc,j}^{t+1} - u_{soc,j}^t + \overline{v}_{soc,j}^t - \underline{v}_{soc,j}^t = 0, t\in[1,23] \tag{7c}$$

$$-u_{soc,j}^{24} + \overline{v}_{soc,j}^{24} - \underline{v}_{soc,j}^{24} = 0 \tag{7d}$$

$$D_{kWh,j} - u_{R,j}^t + \overline{v}_{R,j}^t - \underline{v}_{R,j}^t = 0, \forall t \tag{7e}$$

Complementary slackness:

$$\underline{v}_{soc,j}^t\left(SoC_j^{\min} - SoC_j^t\right) = 0, t\in[1,23] \tag{8a}$$

$$\underline{v}_{soc,j}^{24}\left(SoC_j^{end} - SoC_j^{24}\right) = 0 \tag{8b}$$

$$\overline{v}_{soc,j}^t\left(SoC_j^t - SoC_j^{\max}\right) = 0, \forall t \tag{8c}$$

$$\underline{v}_{R,j}^t R_j^t = 0, \forall t \tag{8d}$$

$$\overline{v_{R,j}^t}\left(R_j^t - R_j^{\max}\right) = 0, \forall t \tag{8e}$$

$$\underline{v_{P_{in,j}}^t} P_{in,j}^t = 0, \forall t \tag{8f}$$

$$\underline{v_{P_{out,j}}^t} P_{out,j}^t = 0, \forall t \tag{8g}$$

Primal feasibility:

$$(1b) - (1i)$$

Dual feasibility:

$$\underline{v_{soc,j}^t}, \overline{v_{soc,j}^t}, \underline{v_{R,j}^t}, \overline{v_{R,j}^t}, \underline{v_{P_{in,j}}^t}, \underline{v_{P_{out,j}}^t} \geq 0 \tag{9}$$

By plugging the KKT conditions into the upper-level problem to replace (2c), it renders the single-level retail pricing problem. It is in a form with (2a) being the objective function and (2b), (2d), (2e), (7a)-(7e), (8a)-(8g), (1b)-(1i), (9) being constraints. According to the new formulation, apart from the nonlinear objective function, additional cross-product terms have been introduced by the complementary slackness conditions. Such non-linearities add great difficulties to the problem. Therefore, two techniques are employed in Sections IV-B and IV-C to linearize the problem.

B. Linearization of the Objective Function

Linearization of the objective function relies on the strong duality property of lower-level problems. Given the strong duality theorem, primal and dual objective functions of the lower-level problems, which are convex, equal to each other at their optimums, as given in (10):

$$\begin{aligned}
&\sum_{t=1}^{24} \beta_{GS}^t (P_{out,j}^t - P_{in,j}^t) - D_{kWh,j} R_j^t \\
&= u_{soc,j}^1 SoC_j^{init} + \sum_{t=1}^{24} \overline{v_{soc,j}^t} SoC_j^{max} - \sum_{t=1}^{23} \underline{v_{soc,j}^t} SoC_j^{min} \\
&\quad - \underline{v_{soc,j}^{24}} SoC_j^{end} + \sum_{t=1}^{24} \overline{v_{R,j}^t} R_j^{max}
\end{aligned} \tag{10}$$

Replacing cross-product terms $\sum_{t=1}^{24} \beta_{GS}^t (P_{out,j}^t - P_{in,j}^t)$ in (2a) using (10) results in the modified objective function (11).

$$\begin{aligned}
&\sum_{t=1}^{24} \alpha^t P_S^t + \sum_{j \in \mathcal{N}_E} (u_{soc,j}^1 SoC_j^{init} + \sum_{t=1}^{24} \overline{v_{soc,j}^t} SoC_j^{max} \\
&- \sum_{t=1}^{23} v_{soc,j}^t \, \mathrm{SoC}_j^{min} - \underline{v_{soc,j}^{24}} \, \mathrm{SoC}_j^{end} + \sum_{t=1}^{24} \overline{v_{R,j}^t} R_j^{max} \\
&+ D_{kWh,j} R_j^t)
\end{aligned} \tag{11}$$

C. Linearization of the Complementary Slackness Constraints

The Big-M method is applied to linearize the complementary slackness conditions [22]. By introducing a sufficiently large constant M and multiple binary variables $\underline{\omega_{soc,j}^t}$, $\overline{\omega_{soc,j}^t}$, $\underline{\omega_{R,j}^t}$, $\overline{\omega_{R,j}^t}$, $\underline{\omega_{Pin,j}^t}$, $\underline{\omega_{Pout,j}^t}$, (8a)-(8g) are then converted into pairs of inequality constraints, where the binary variable controls whether the upper bound of each inequality constraint is hit or not.

TABLE I
BATTERY PARAMETER CONFIGURATION

Parameter	Definition
C	210 kWh
l_c	4 %
l_d	4.5 %
SoC_{min}	20 %
SoC_{max}	80 %
R_{max}	50 kW
D_{kWh}	0.005 $/kWh

$$0 \leq \underline{v_{soc,j}^t} \leq \underline{\omega_{soc,j}^t} M, \quad t \in [1, 23] \tag{12a}$$

$$0 \leq SoC_j^t - SoC_j^{\min} \leq \left(1 - \underline{\omega_{soc,j}^t}\right) M, \quad t \in [1, 23] \tag{12b}$$

$$0 \leq \underline{v_{soc,j}^{24}} \leq \underline{\omega_{soc,j}^{24}} M \tag{12c}$$

$$0 \leq SoC_j^{24} - SoC_j^{end} \leq \left(1 - \underline{\omega_{soc,j}^{24}}\right) M \tag{12d}$$

$$0 \leq \overline{v_{soc,j}^t} \leq \overline{\omega_{soc,J}^t} M, \quad \forall t \tag{12e}$$

$$0 \leq SoC_j^{\max} - SoC_j^t \leq (1 - \overline{\omega_{soc,j}^t}) M, \quad \forall t \tag{12f}$$

$$0 \leq \underline{v_{R,j}^t} \leq \underline{\omega_{R,j}^t} M, \quad \forall t \tag{12g}$$

$$0 \leq R_j^t \leq \left(1 - \underline{\omega_{R,j}^t}\right) M, \quad \forall t \tag{12h}$$

$$0 \leq \overline{v_{R,j}^t} \leq \overline{\omega_{R,j}^t} M, \quad \forall t \tag{12i}$$

$$0 \leq R_j^{\max} - R_j^t \leq \left(1 - \overline{\omega_{R,j}^t}\right) M, \quad \forall t \tag{12j}$$

$$0 \leq \underline{v_{Pin,j}^t} \leq \underline{\omega_{Pin,j}^t} M, \quad \forall t \tag{12k}$$

$$0 \leq P_{in,j}^t \leq \left(1 - \underline{\omega_{Pin,j}^t}\right) M, \quad \forall t \tag{12l}$$

$$0 \leq \underline{v_{Pout,j}^t} \leq \underline{\omega_{Pout,j}^t} M, \quad \forall t \tag{12m}$$

$$0 \leq P_{out,j}^t \leq \left(1 - \underline{\omega_{Pout,j}^t}\right) M, \quad \forall t \tag{12n}$$

$$\underline{\omega_{soc,j}^t}, \overline{\omega_{soc,j}^t}, \underline{\omega_{R,j}^t}, \overline{\omega_{R,j}^t}, \underline{\omega_{Pin,j}^t}, \underline{\omega_{Pout,j}^t} \in \{0, 1\} \tag{12o}$$

After jointly applying techniques presented in Section IV, the day-ahead retail pricing problem is now fully transformed into a MILP problem. It targets at minimizing (11) while subjecting to (2b), (2d), (2e), (7a)-(7e), (12a)-(12o), (1b)-(1i), (9).

V. CASE STUDY

To illustrate how the retail market pricing scheme performs, a comprehensive case study is carried out simulating a retail market with up to 20 batteries and 30 inflexible loads. Inflexible loads sum up to a daily system inflexible load portfolio ranging between 594.22 kWh and 1009.37 kWh. Batteries are parameterized identically according to Table I, taking the Tesla Powerpack 210 kWh model as the reference [23]. The $SoCs$ of batteries at

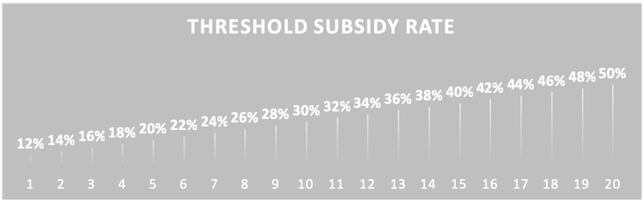


Fig. 4. Threshold subsidy rate.

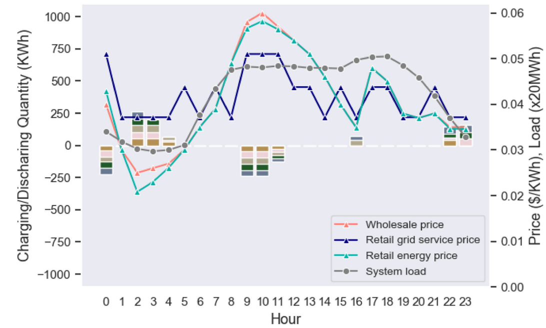
TABLE II
FINANCIAL ANALYSES UNDER DIFFERENT SUBSIDY RATES

δ_{sub}	Total System Cost ($)	Total Electricity Bill Saving ($)	Total Gross Revenue ($)	Total Discounted Revenue ($)
0%	850.76	0.00	0.00	0.00
20%	843.57	7.20	10.44	1.80
30%	838.30	12.46	22.49	5.34
40%	834.40	16.36	36.56	10.90
50%	831.82	18.94	52.11	18.94

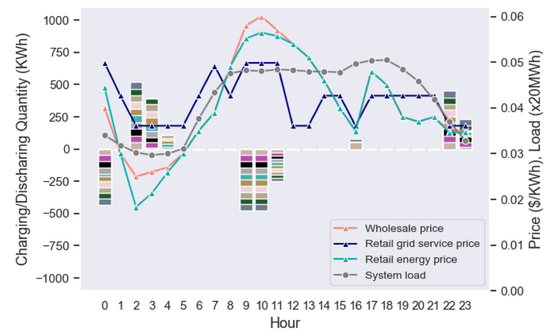
the beginning of the day are randomly initialized. In addition, elastic participants who own these batteries are with different threshold subsidy rates, which means their willingness to participate in the retail market varies against the system subsidy rate, δ_{sub}, as illustrated in Fig. 4. For instance, when $\delta_{sub} = 34\%$, No.1-12 batteries are willing to join the retail market. M and C_β are set to be 10000 and 1$/kWh in the case study. The retail pricing problem is jointly solved using Pyomo [24], an extensible Python-based open-source optimization modeling language, and Gurobi [25], a commercial mathematical optimization solver.

A. Rationale of Market Participants

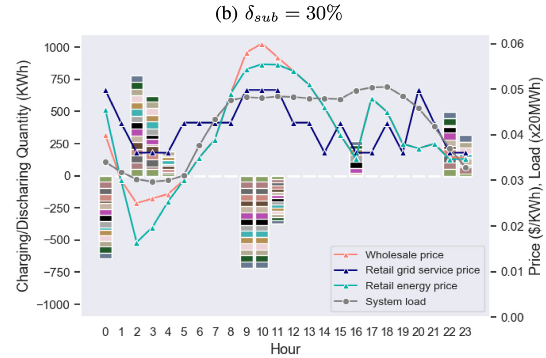
The rationale of various market players to participate in the retail market is first verified. Fig. 5(a)–(d) plot optimal market solutions obtained when δ_{sub} equals to 20%, 30%, 40% and 50%, and correspondingly 5, 10, 15 and 20 batteries join the retail market. Gray and orange curves illustrate fluctuations of the system-level inflexible load and wholesale price over a day. Navy and light blue curves indicate the optimized retail grid service price and retail energy price. Bar blocks in different colors represent optimized charging (above the horizontal axis) and discharging (below the horizontal axis) quantities of different battery under the incentive of the retail grid service price. Corresponding day-ahead financial settlements for these four cases are calculated in Table II, from aspects of total system cost, total electricity bill saving for inflexible loads, and total gross/discounted revenues made by batteries. According to Fig. 5, the retail energy price is lower than the wholesale price for most time in the day. When the subsidy rate δ_{sub} becomes higher and more batteries are in the market, the gap between the wholesale price and the retail energy price becomes wider. Correspondingly, the total electricity bill for inflexible loads drops by up to $18.94, as indicated in Table II. It justifies the rationale of inelastic participants to participate in the retail market as they could enjoy a lower electricity price compared to directly purchasing their fixed demands at the wholesale price.



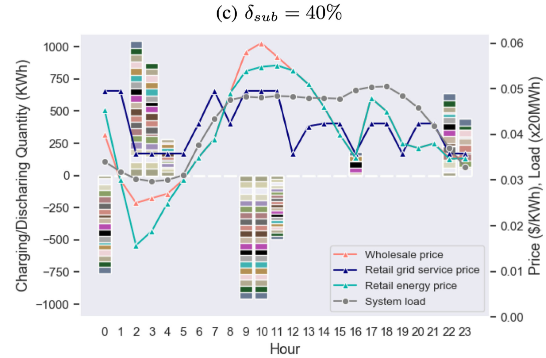
(a) $\delta_{sub} = 20\%$



(b) $\delta_{sub} = 30\%$



(c) $\delta_{sub} = 40\%$



(d) $\delta_{sub} = 50\%$

Fig. 5. Optimal retail market solutions under different subsidy rates.

On the other hand, according to Table II, both total gross revenue (i.e., sum of grid service income and subsidy) and total discounted revenue (i.e., gross revenue subtracts degradation cost) made by batteries are above zero. In other words, the retail energy price is not lowered at the expense of battery owners' sacrifices, which further validates the rationale of elastic participants to participate in the market. Similarly, a higher subsidy rate

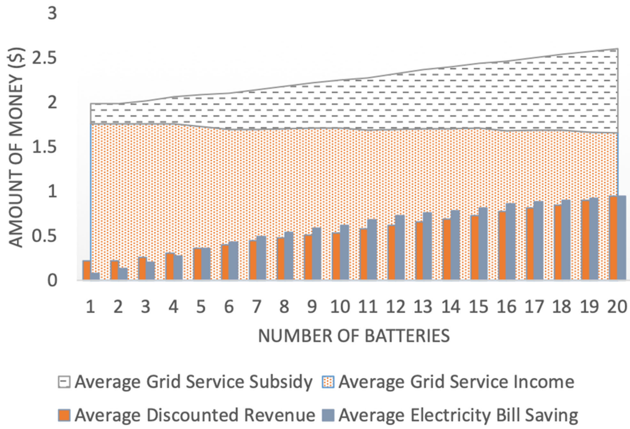


Fig. 6. Market settlement results under different numbers of batteries.

contributes to a greater total gross/discounted revenue earned by elastic participants. Despite the increased number of elastic participants to share the revenue, the averaged gross/discounted revenue for individual elastic participant still grows monotonically as the subsidy rate raises.

B. Benefits of Adding the Grid Service Subsidy

To better understand the role that the grid service subsidy plays in the retail market, financial benefits achieved per inflexible load and battery are calculated and illustrated in Fig. 6. Stacked area plots in Fig. 6 represent how the breakdowns of averaged gross revenue: averaged grid service income and averaged grid service subsidy, vary under different numbers of batteries. Bar plots in Fig. 6, on the other hand, indicate variations of the averaged discounted revenue and averaged electricity bill saving under different number of batteries. Note that averaged gross and discounted revenues reflect the short-term and long-term profitability of a battery participating in the retail market.

According to Fig. 6, it is found that under the proposed retail pricing scheme, both short-term and long-term financial benefits enjoyed per battery improve as the number of batteries grows, same for the electricity bill saving shared per inflexible load. Nevertheless, assuming there is no grid service subsidy, the averaged gross revenue then equals to the averaged grid service income, which decreases as a result of increased batteries participation. Moreover, the averaged discounted revenue would reduce to almost zero due to the considerable degradation effect of batteries. Therefore, without the grid service subsidy, from a short-term perspective, less batteries will be encouraged to join the market as other batteries' participation harms the benefit of existing batteries due to a severer competition; from a long-term perspective, no incentive will be actually given to a rational battery owner. In other words, the addition of the grid service subsidy ensures the long-term profitability of elastic participants and compensates the loss of their short-term profitability brought up by the competition. Such a subsidy seems to compromise the benefit of inelastic participants, however, would ultimately secures it.

TABLE III
FINANCIAL ANALYSES UNDER FOUR DIFFERENT RETAIL PRICING SCHEMES

	Total Electricity Bill Saving ($)	Total Gross/Discounted Revenue ($)	RMO Profit ($)
Profit-neutral & double-signal [2].	18.94	52.11 / 18.94	0.00
Profit-oriented & double-signal [3]	-81.19	33.17 / 0.00	119.06
Profit-oriented & single-signal [4]	-20.55	82.64 / 57.44	52.32

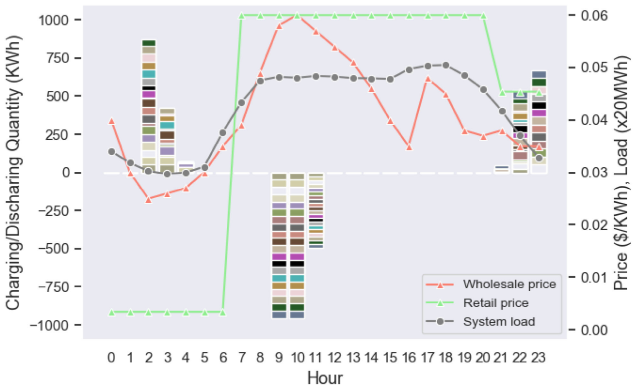
[2]Problem formulation is given in (2) in Section III
[3]Problem formulation is given in (14) in Appendix A
[4]Problem formulation is given in (15) in Appendix A

Fig. 6 also provides a guidance for the RMO to reasonably select the subsidy rate, δ_{sub}. According to Fig. 6, under the threshold subsidy rate preference assumed in Fig. 4, it is most beneficial to set δ_{sub} as 50%, since it maximizes the averaged benefits for both elastic and inelastic participants. Similar analyses can be conducted by drawing this graph given different market settings.

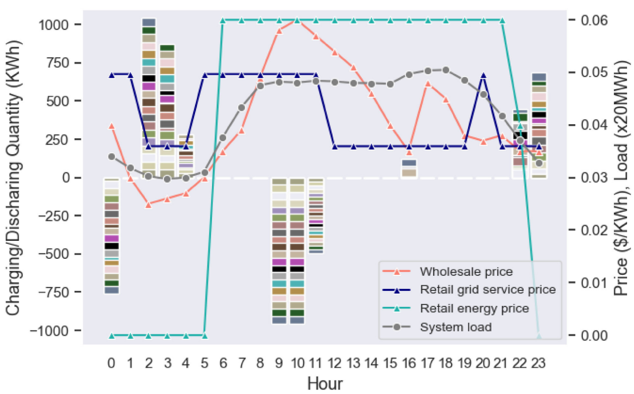
C. Proposed Retail Pricing Scheme vs. Alternatives

Finally, to justify advantages of the proposed retail pricing scheme over other alternatives, we conducted another numerical experiment comparing pricing solutions and financial settlements obtained under four pricing schemes (including the proposed one) categorized based on: 1) the number of price signals (i.e., single-signal or double-signal) and 2) profitability of the RMO (i.e., profit-neutral or profit-oriented): We distinguish between single-signal and double-signal pricing schemes based on whether both price-sensitive customers (e.g., batteries) and price-insensitive customers (e.g., non-flexible loads) are charged/credited by a same price signal or two separate price signals; We distinguish between profit-oriented and profit-neutral pricing schemes based on the relation between (A) the total payment paid by non-flexible loads and (B) the total cost paid to the wholesale market and batteries. The pricing scheme enforcing $A = B$ and minimizing B is considered as profit-neutral, whereas the pricing scheme maximizing the gap between A and B is considered as profit-oriented. For detailed problem formulations of three alternatives, please refer to Appendix A.

Fig. 7 plots pricing solutions obtained from the profit-oriented & single-signal and profit-oriented & double-signal pricing schemes. Similar legends are applied as of in Fig. 5, except that we use light green curve in Fig. 7(a) to distinguish the retail price applied under the single-signal pricing scheme from grid service and energy prices applied under the double-signal pricing scheme. Table III summarizes financial outcomes obtained under these four pricing schemes. Note that results corresponding to the profit-neutral & single-signal alternative are not available either in Fig. 7 or Table III. It is because the demand-supply balance constraint (13b), revenue-cost balance constraint (13c), and constraint on the sum of grid service prices over a day (13e) required by the problem formulation (13) cannot be satisfied at the same time in general.



(a) Profit-oriented and single-signal



(b) Profit-oriented and double-signal

Fig. 7. Market solutions under alternative pricing schemes

According to Fig. 7 and Table III, several key observations can be obtained:

1) In comparison with the profit-neutral pricing scheme proposed in this study (see Fig. 5(d)), profit-oriented pricing schemes tend to be dominated by the system load (indicated by the gray curves in Fig. 7) as highest possible price (price cap, set as 0.06 $/kWh) is assigned to hours with greater energy consumption. Consequently, inflexible loads need to pay at a higher price than the wholesale market price, indicating a poor system efficiency. Although batteries and the RMO are benefited with high revenues, such profit-oriented pricing schemes are not sustainable, as the high revenues are gained by sacrificing inflexible loads and the system efficiency
2) By further comparing between the single-signal and double-signal profit-oriented pricing schemes, it is observed that a higher profit is achieved by the RMO under the single-signal pricing scheme. It is because these two price signals are not financially binding in the profit-oriented market, such that the RMO has more controls over the price signals to specifically maximize its benefit from each type of participants. Such a controllability, however, is restricted under the profit-oriented single-signal pricing scheme.

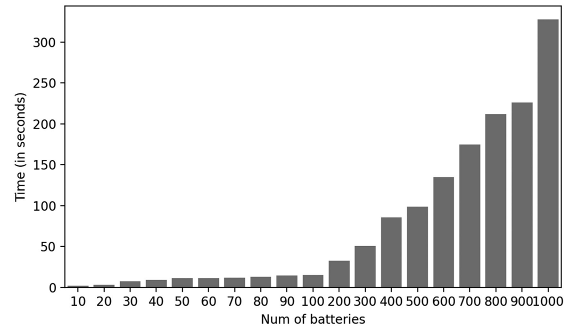


Fig. 8. Computation time (in seconds) with different numbers of batteries.

3) In comparison with other alternatives, the profit-neutral double-signal retail pricing scheme proposed in this study demonstrates the most promising properties. Most importantly, it ultimately benefits both types of market participants and the system efficiency. In addition to that, the retail energy price signal generated under the proposed retail pricing scheme is more dynamic and better represents the real system operating status over time.

D. Computational Efficiency and Scalability

To test computational efficiency and scalability of the proposed retail pricing scheme, we conduct another sensitivity analysis in which computation time for solving the bi-level optimization has been recorded under the participation of varying numbers of batteries. The experiment is conducted using a laptop with a 2.8 GHz Quad-Core i7 processor and 16 GM memory. Fig. 8 illustrates the computation time when the number of batteries changes from 10 to 1000 with an increment of 10 when the number is below 100 and with an increment of 100 when the number exceeds 100.

According to Fig. 8, the proposed pricing scheme demonstrates great computational performance and scalability. It takes less than one minute to solve the pricing problem with up to 300 batteries. When the number of batteries reaches 1000, the computation time goes up to 327 seconds, which is still computational affordable given that this pricing scheme is implemented in the day-ahead market.

VI. Conclusion and Future Work

In this study, a profit-neutral double-signal retail pricing scheme is proposed tailored for batteries considering their price-responsive nature and inter-temporal operational constraints. Case studies demonstrate advanced properties of the proposed retail pricing tool. First of all, it is able to separately capture and monetize the values provided by batteries or other elastic assets for boosting the system efficiency. Second of all, such a retail pricing scheme is beneficial for market participants both sensitive and insensitive to the market price, providing the proper incentive for rational market players to join. Furthermore, due to the addition of grid service subsidy, benefits enjoyed by inflexible loads and batteries are secured both in short-term and long-term. Last but not least, compared to other alternatives, it is more sustainable and capable of representing the system operating status. Above all, the profit-neutral double-signal retail pricing solution offers a promising start for reconstructing the retail electricity market from a conceptual perspective. In practice, we expect the retail pricing scheme to be applied in day-ahead for short-term distribution system operation planning and facilitating the bidding of RMO into the wholesale market. The bidding process and its interactions with the wholesale market will be investigated in future work, in addition to the development of a real-time pricing scheme that cooperates with the day-ahead pricing scheme to address the DA-RT imbalance.

Appendix A
Problem Formulations of Alternative Pricing Schemes

Problem formulation of the profit-neutral & single-signal pricing scheme:

$$\underset{\boldsymbol{\beta},\boldsymbol{P_{out}},\boldsymbol{P_{in}}}{\textbf{minimize}} \quad \sum_{t=1}^{24}\alpha^t P_S^t + \sum_{t=1}^{24}\sum_{j\in\mathcal{N}_E}\beta^t\left(P_{out,j}^t - P_{in,j}^t\right)$$

$$\textbf{subject to} \tag{13a}$$

$$P_S^t + \sum_{j\in\mathcal{N}_E}\left(P_{out,j}^t - P_{in,j}^t\right) = \sum_{i\in\mathcal{N}_I}P_{L,i}^t, \forall t \tag{13b}$$

$$\sum_{t=1}^{24}\alpha^t P_S^t + \sum_{t=1}^{24}\sum_{j\in\mathcal{N}_E}\beta^t\left(P_{out,j}^t - P_{in,j}^t\right) = \sum_{t=1}^{24}\sum_{i\in\mathcal{N}_I}\beta^t P_{L,i}^t, \forall t \tag{13c}$$

$$\boldsymbol{P_{out,j}}, \boldsymbol{P_{in,j}} := \underset{\boldsymbol{X_j}}{argmax}\{f_j(\boldsymbol{X_j},\boldsymbol{\beta}) : g_j(\boldsymbol{X_j}) \le 0, h_j(\boldsymbol{X_j}) = 0\}, j\in\mathcal{N}_E \tag{13d}$$

$$\sum_{t=1}^{24}\beta^t = C_\beta \tag{13e}$$

$$\beta^t \ge 0, \forall t \tag{13f}$$

Problem formulation of the profit-oriented & double-signal pricing scheme:

$$\underset{\boldsymbol{\beta_E},\boldsymbol{\beta_{GS}},\boldsymbol{P_{out}},\boldsymbol{P_{in}}}{\textbf{maximize}} \quad \sum_{t=1}^{24}\beta_E^t P_L^t - \sum_{t=1}^{24}\alpha^t P_S^t - \sum_{t=1}^{24}\sum_{j\in\mathcal{N}_E}\beta_{GS}^t\left(P_{out,j}^t - P_{in,j}^t\right)$$

$$\textbf{subject to} \tag{14a}$$

$$P_S^t + \sum_{j\in\mathcal{N}_E}\left(P_{out,j}^t - P_{in,j}^t\right) = \sum_{i\in\mathcal{N}_I}P_{L,i}^t, \forall t \tag{14b}$$

$$\boldsymbol{P_{out,j}}, \boldsymbol{P_{in,j}} := \underset{\boldsymbol{X_j}}{argmax}\left\{f_j(\boldsymbol{X_j},\boldsymbol{\beta_{GS}}) : g_j(\boldsymbol{X_j}) \le 0, h_j(\boldsymbol{X_j}) = 0\right\}, j\in\mathcal{N}_E \tag{14c}$$

$$\sum_{t=1}^{24}\beta_{GS}^t = C_\beta \tag{14d}$$

$$\beta_{GS}^t \ge 0, \forall t \tag{14e}$$

Problem formulation of the profit-oriented & single-signal pricing scheme:

$$\underset{\boldsymbol{\beta},\boldsymbol{P_{out}},\boldsymbol{P_{in}}}{\textbf{maximize}} \quad \sum_{t=1}^{24}\beta^t P_L^t - \sum_{t=1}^{24}\alpha^t P_S^t - \sum_{t=1}^{24}\sum_{j\in\mathcal{N}_E}\beta^t\left(P_{out,j}^t - P_{in,j}^t\right)$$

$$\textbf{subject to} \tag{15a}$$

$$P_S^t + \sum_{j\in\mathcal{N}_E}\left(P_{out,j}^t - P_{in,j}^t\right) = \sum_{i\in\mathcal{N}_I}P_{L,i}^t, \forall t \tag{15b}$$

$$\boldsymbol{P_{out,j}}, \boldsymbol{P_{in,j}} := \underset{\boldsymbol{X_j}}{argmax}\left\{f_j(\boldsymbol{X_j},\boldsymbol{\beta}) : g_j(\boldsymbol{X_j}) \le 0, h_j(\boldsymbol{X_j}) = 0\right\}, j\in\mathcal{N}_E \tag{15c}$$

$$\sum_{t=1}^{24}\beta^t = C_\beta \tag{15d}$$

$$\beta^t \ge 0, \forall t \tag{15e}$$

Appendix B
Omission of the Charging and Discharging Complementary Constraint

We prove that any solution with simultaneous battery charging and discharging operation is suboptimal to (1) (after omitting (1j)) utilizing the KKT conditions of (1), inspired by [26].

Let's assume there is a time $t=\tau$ when $P_{out,j}^\tau > 0$ and $P_{in,j}^\tau > 0$ is the optimal solution of the problem. Given that problem (1) (after omitting (1j)) is a convex problem, any optimal solution of (1) would satisfy the KKT conditions: (7), (8) (1b)-(1i), (9). Combining the complementary slackness conditions (8f) and (8g) at time $t=\tau$ with the assumption we made on $P_{out,j}^\tau > 0$ and $P_{in,j}^\tau > 0$, we have Lagrange multipliers associated with (1h) and (1i) at time $t=\tau$ equal to zero: $\underline{v_{P_{in,j}}^\tau} = 0$ and $\underline{v_{P_{out,j}}^\tau} = 0$

By plugging the value of $\underline{v_{P_{in,j}}^\tau}$ and $\underline{v_{P_{out,j}}^\tau}$ into the stationarity conditions (7a) and (7b) at time τ and removing the common variable $u^{\tau}_{soc,j}$, it renders:

$$\beta^{\tau}_{GS}(l_{d,j} + l_{c,j} - l_{d,j}l_{c,j}) + 2u^{\tau}_{R,j}(1 - l_{c,j}) = 0 \quad (16)$$

In addition, given equality constraints (1d), complementary slackness conditions (8d) and dual feasibility (9), we have $R^{\tau}_{j} > 0$, $\underline{v^{\tau}_{R,j}} = 0$ and $\overline{v^{\tau}_{R,j}} \geq 0$. Based on the above conditions along with constraint (7e) at time τ, we also have $u^{\tau}_{R,j} > 0$. This condition together with the assumption we made on the sign of the grid service price ($\beta^{\tau}_{GS} \geq 0$), however, contradict with the statement (16), indicating that any solution with simultaneous charging and discharging operation is suboptimal to problem (1). Therefore it is proven that the omission of (1j) will not affect the optimal solution of (1) as long as $\beta^{t}_{GS} \geq 0, \forall t$, which has been added in the upper-level problem (2) as an additional constraint (2e).

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