An Occupancy-Informed Customized Price Design for Consumers: A Stackelberg Game Approach

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***Abstract*—Residential occupancy patterns are closely tied with consumers' activities and can potentially be leveraged to improve demand response by identifying the periods when high demand occurs. Occupancy detection can be generally divided into two categories in existing studies: intrusive and non-intrusive detection. However, both methods are still challenging to implement in practice, due to privacy concerns raised by intrusive sensors and the lack of labeled data required by non-intrusive methods. This paper seeks to design customized prices based on different consumers' occupancy status and consumption patterns to enhance both retailer and consumers' benefits using smart meter data. The interaction between the retailer and consumers is modeled as a one-leader-N-follower Stackelberg game. A two-stage decision-making framework, including day-ahead and real-time, is proposed for revenue maximization. The ECO (Electricity Consumption and Occupancy) Swiss households dataset is adopted to evaluate the effectiveness of the proposed occupancy-informed demand response program design.**

***Index Terms*—Occupancy, game theory, customized price design, demand response.**

NOMENCLATURE

Indices and Sets

h	Time index, $h \in \{1, 2, 3, \ldots, H\}$.
i	Consumer's index, $i \in \{1, 2, 3, \ldots, I\}$.
m	Index of ToU segments, $m \in \{1, 2, \ldots, M\}$
$\mathbf{U}$	Set of all consumers' utilities.
$\mathbf{U}_i$	Aggregated daily utility of consumer i.
$\mathbf{P}$	Set of the customized prices for consumers.
$\mathbf{L}$	Set of all consumers' aggregated loads.
$\mathbf{sl_i}, \mathbf{fl_i}, \mathbf{l_i}$	Set of consumer i's shiftable loads, fixed loads, and aggregated loads in a day.

Parameters

a, b, c	Generation parameters.
O_i^h	Occupancy status of consumer i at time h.
D_{min}	Minimum duration of each ToU segment.
p_0	Baseline price for consumers.
p_{min}/p_{max}	Lower/upper bound of the customized prices.
γ	A sufficient large number.
p_{Uti}	Utility rate.
p_{Fit}	Feed-in-tariff.
k_i^h	Consumption preference coefficient of consumer i at time h.
$\mathbf{N}_{ave}$	Average power over a time window in occupancy inference.
$\mathbf{N}_{mm}$	Power range over a time window in occupancy inference.

Variables

p_i^h	Customized price for consumer i at time h.
L^h	Aggregated load of all consumers at time h.
l_i^h	Aggregated load of consumer i at time h.
fl_i^h	Fix load of consumer i at time h.
sl_i^h	Shiftable load of consumer i at time h.
$\lambda_i^{m,h}$	A binary variable. $\lambda_i^{m,h} = 1$ indicates price p_i^h belongs to block m, or else $\lambda_i^{m,h} = 0$.
$p_i^{m,h}$	Price for consumer i in block m at time h.
$\Omega_i^{m,h}$	A binary variable product $\lambda_i^{m,h} \times p_i^{m,h}$.
ΔL^h	Imbalance of aggregated supply and demand between day-ahead and real-time markets at time h.
δ_i^h	Real-time load deviation of consumer i at time h.

Functions & Operators

U_i	Utility function of consumer i.
R	Revenue of the retailer.
C_g	Generation cost of the retailer in the day-ahead market.
C_b	Balancing cost of the retailer in the real-time market.
$(\hat{\bullet})$	Variables at the day-ahead stage.
$(\tilde{\bullet})$	Variables at the real-time stage.

Acronym

DR	Demand response.
DA, RT	Day-ahead and real-time.
ToU	Time-of-use price.
RTP	Real-time price.
NILM	Non-intrusive load monitoring.

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ECO	Electricity consumption and occupancy.
PDR	Probability of demand response.
GTO	Ground-truth occupancy.
IO	Inferred occupancy.
RT-GTO	Scenario with ground-truth occupancy.
RT-IO	Scenario with inferred occupancy.
TP, TN	True positive, true negative of occupancy inference, true indicates right inference.
FP, FN	False positive, false negative of occupancy inference, false indicates wrong inference.

I. Introduction

SMART meters can provide utility companies with detailed high-quality electricity consumption information. Large utility companies have increasingly installed smart meter systems across the U.S. A 2019 Federal Energy Regulatory Commission staff report [1] indicates a nationwide 60.3% penetration rate of smart meter in 2019. For utility companies, smart metering could improve large-scale load planning and long-term research through real-time energy consumption feeds. For example, smart meter data has been widely used to estimate the satisfaction of the consumer, predict consumer behaviors and preferences, disaggregate the behind-the-meter data, and detect power outages [2]. For consumers, the smart meter could potentially help lower electricity costs, provide more information about consumption patterns, and enhance the ability to actively participate in demand response (DR).

A successful price-based DR scheme should be designed to attract the interest of consumers in participating in the program, through the provision of incentives to change their conventional power consumption habits, while at the same time minimizing the consumers' discomfort. The key principle of the customized price design is ***incentive compatible*** [3], which is a mechanism proven to be efficient for each agent to act based on its best strategy. In electricity markets, different types of time-varying pricing approaches have already been proposed to provide consumers with incentives of DR, among which time-of-use (ToU) price and real-time price (RTP) are the most widely adopted ones. Different price signals always provide consumers a marginal price signal regarding the cost for one more kWh of electricity, as seen in the Olympic Peninsula project [4]. Extensive work has been performed in the literature to solve the problem of price-based DR program. For example, [5] utilized mixed integer linear programming to solve the DR program. In [6], a Model Predictive Control scheme was applied to optimize load management. Recently, there have been growing interests in adopting game theory to model DR problems in smart grids [7]. For example, as a most widely used game approach, a Nash equilibrium-based game-theoretic approach was applied in price-based DR problem among storage units [8], multiple prosumers [9], and distributed energy resource owners [10]. Moreover, a leader-follower Stackelberg game was applied to describe the competitive situation between microgrids and a utility grid [11], a combined heat and power community [12], residential units and shared facility controllers [13], and retailers and consumers [14]. Most of these works are built in a day-ahead (DA) market, and once the optimal strategy is determined, each player must follow the strategy in the real-time (RT) stage. However, there generally exists a large gap between DA and real-time supply/demand and prices. To manage the uncertainty in DA and RT markets, researchers in [15], [16] proposed a two-stage decision-making framework. A real-time Stackelberg-based DR algorithm was presented to address the energy consumption management problem in a facility considering RTPs [17]. Although a significant amount of effort has been performed to solve the problem of DR program realization, the impacts of occupancy have not yet been considered in previous studies.

Occupancy detection in commercial or residential buildings has been researched extensively in recent years. The occupancy status could dynamically affect the time window and capability of a consumer to participate in demand response. Occupancy detection could help DR program design in three aspects: (i) determining peak demand periods at the household level, (ii) identifying the ability of consumer to participate in DR, and (iii) operating appliances remotely and automatically.

Occupancy detection can be roughly categorized into intrusive or non-intrusive groups based on the monitored objects. Intrusive occupancy detection can be achieved via the use of various sensor types, such as surveillance videos [18], indoor environments [19], water meters [20], WiFi [21], etc. However, the extensive deployment of intrusive occupancy detection is challenging due to the high installation costs, additional operation requirements (e.g., image processing for cameras), and privacy concerns. Compared to intrusive approaches, non-intrusive methods raise fewer privacy concerns. The fast-growing penetration of smart meters has enabled the advancement of data analytics approaches for non-intrusive occupancy detection solely through smart meter data. For example, a collection of machine learning models have been applied in occupant behavior detection in the literature [22], [23], [24], [25], such as decision tree, support vector machine, K-nearest neighbor, random forest, hidden Markov model, convolutional neural network, and long short-term memory. Nevertheless, non-intrusive occupancy detection is still suffering from several limitations such as extra data collection/processing, unsatisfactory accuracy, low infrastructure/device coverage, and its practical applicability. Specifically, in practice, personal ground-truth occupancy labels may not be publicly available. In addition, occupancy may not directly imply consumers' willingness to participate in DR programs.

While occupancy detection could be used in many ways such as building energy management, the impact of occupancy detection on DR has not been studied in the literature. Building upon existing literature, this paper seeks to bridge the gap between residential occupancy and its application in DR. The main contributions of this paper include:

- A customized pricing mechanism is proposed to incentivize consumers to participate in the DR program established by the retailer, since different consumers may have varying daily consumption preferences.
- Occupancy patterns are modeled and considered in conjunction with DR to investigate consumers' consumption

behavior. The effectiveness of two different occupancy labels, i.e., ground-truth and inferred occupancy, is analysed to study the interaction between the retailer and consumers.

- A two-stage decision-making process is developed to maximize the economic revenue of the retailer while maintaining the consumers' benefits. In the first DA stage, the objective is to design an optimal ToU structure. In the second RT stage, a one-leader-N-follower Stackelberg game is applied to address the uncertainty and determine the final equilibrium price.

The remainder of this paper is organized as follows. Section II describes the framework of the energy retail market. The developed occupancy-informed retailer's customized pricing model is formulated in Section III. Section IV introduces the consumers' consumption model, and Section V describes the game-based RTP design. Section VI summarizes and briefly analyzes the publicly available dataset adopted in our case study, followed by results and discussion in Section VII. Section VIII concludes the paper and discusses the future work.

II. System Framework

We consider a local retail market consisting of a retailer and I consumers with an energy management system and DR capabilities. The market works in an agent-based trading mode: the retailer supplies all consumers with the customized prices; besides, the retailer also acts as an agent between the utility grid and local consumers, and is responsible for balancing the supply and demand in the local market. The consumer's energy management system is an intelligent automated control system that dynamically records smart meter data, analyzes and predicts energy consumption, schedules and controls appliances with respect to different price signals based on users' consumption preferences.

To mitigate the price risks of both ToU/RTP and ensure the profits of the retailer and all consumers, a two-stage price design framework is proposed in this work.

1) Stage I: DA stage. The ToU price is designed in the DA stage by following the principle of ***incentive compatible*** [3], [14], which ensures the utilities that consumers receive under the new prices are better than the old ones.
2) Stage II: RT stage. The RTP is determined in the RT stage to hedge against price volatility and maintain a trustful RT market through a price bargaining scheme [15], [17].

A. Stage I: DA Stage

1) The Retailer: The DA stage helps the retailer design customized ToU pricing schemes and determine the generation schedule with the goal of revenue maximization. Using the DA load data collected from the customers, the retailer extracts different consumption preferences of customers, and then publishes the DA ToU prices to the customers before the operating day. The main role of ToU is to: i) provide a basic incentive signal to customers, and ii) set a basic boundary for RTP to help avoid price volatility.

2) The Consumers: All consumers are assumed to act rationally and strategically to pursue their own interests, e.g., maximizing their utilities in this work. As long as the utilities they receive under the new prices are better than the old ones, participating in the customized price design program is a better choice for these consumers. This constraint emphasizes the benefits of the consumers, which reduces the risk of DA ToU. After the consumers receive the DA ToU price signals from the retailer, they initialize their energy consumption schedules based on their best DR strategies, which is optimized based on their ground-truth consumption preferences and occupancy status.

B. Stage II: RT Stage

1) The Retailer: It is common that there always exists differences between DA and RT due to imperfect forecasts and increased customers' DR activities. The retailer determines the personalized RTPs to incentivize the consumers to adjust their flexible consumption with the aim of balancing the supply and demand in the local market. An penalty rule is designed by the retailer to mitigate the price risk and maintain a trustful market. The penalty terms establishes the final acceptable range for the RTP signals based on the violation between customers' RT consumption and DA load.

2) The Consumers: After initializing the consumption after the DA stage, the consumers will also react to the customized RTP signals designed by the retailer. Since each consumer has various occupancy status, consumption satisfaction level, and consumption range, its ability of load shifting is also different. Customized RTP signals are expected to distinguish this difference and prioritize the consumers based on their DR abilities. Besides, how the occupancy status impacts the interaction between the retailer and consumers will also be explored.

III. Retail's Pricing Model

This section describes the retailer's pricing strategies in DA and RT stages. It is noted that to distinguish the DA stage from the RT in this section, variables in the DA stage are noted with a hat symbol ($\hat{\bullet}$), and variables in the RT stage are noted with a tilde symbol ($\tilde{\bullet}$).

A. DA ToU Design

The DA ToU price allows buyers and sellers to hedge against price volatility in the RT operation by locking energy prices in a specific range before the operating day. In the DA stage, the retailer (seller) designs customized ToU prices for consumers (buyers) in order to maximize its revenue, which follows the following two design principles:

- Each ToU scheme has $m = 1, 2, \ldots, M$ segments ($M \leq 3$ in this paper, which can be extended), the minimum duration (D_{min}) for each block is 2 h, and the designed price for consumer i in each block (p_i^m) is constrained in a specific range $[p_{min}, p_{max}]$ (i.e., [\$0.05, \$0.8], also applies to RTP in this paper);

$$p_{min} \leq \hat{p}_i \leq p_{max} \tag{1}$$

- For consumer i, the newly designed pricing scheme (p_i) should generate a higher aggregated daily utility ($\mathbf{U_i}$) compared to the utility under the original price (p_0), which ensures its willingness of participating in the new ToU prices.

$$\mathbf{U_i}(\hat{p}_i) \geq \mathbf{U_i}(p_0) \tag{2}$$

$$\mathbf{U_i}(p_i) = \sum_{h=1}^{H=24} U_i^h\left(p_i^h\right) \tag{3}$$

Besides, the consumers are also allowed to reschedule their consumption to pursue a higher utility by shifting their consumption under the newly designed rate. The utility function (U_i^h) will be introduced in Section IV-A.

The DA ToU price design model is formulated by following [14], which is briefly described as follows.

$$\sum_{m=1}^{M} \lambda_i^{m,h} = 1 \tag{4}$$

$$\sum_{h=1}^{H} \lambda_i^{m,h} \geq D_{min}, \forall m, i \tag{5}$$

$$\left|\lambda_i^{m,H} - \lambda_i^{m,1}\right| + \sum_{h=2}^{H}\left|\lambda_i^{m,h-1} - \lambda_i^{m,h}\right| = 2, \forall m, i \tag{6}$$

$$p_i^h = \sum_{m=1}^{M} \lambda_i^{m,h} \times p_i^{m,h}, \forall m, i \tag{7}$$

where H is the whole optimization horizon (i.e., 24 h); h is the current time slot. The term $\lambda_i^{m,h}$ is a binary variable; $\lambda_i^{m,h} = 1$ if time h locates in block m, or else $\lambda_i^{m,h} = 0$. Eq. (4) indicates that there only exists one price in a single time interval, and Eq. (5) ensures the minimum duration of each block. Eq. (6) restricts that each scheme only has two changes at most. Finally, the ToU price p_i^h for consumer i in time h is given by Eq. (7). In the solving process, the binary variable product in Eq. (7) is eliminated as follows:

$$\Omega_i^{m,h} \leq \gamma \times \lambda_i^{m,h}, \Omega_i^{m,h} \leq p_i^{m,h} \tag{8}$$

$$\Omega_i^{m,h} \geq p_i^{m,h} - \gamma \times \left(1 - \lambda_i^{m,h}\right), \Omega_i^{m,h} \geq 0 \tag{9}$$

where $\Omega_i^{m,h}$ denotes the binary variable product in Eq. (7). As a result, the binary variable product is eliminated by introducing a sufficient large number γ (also known as the big-M method).

Based on the practical grid operation, the cost function is assumed to be: i) monotonously increasing with the aggregated energy, and ii) strictly convex. To this end, the following quadratic cost function $C_g^h(\hat{L^h})$ is adopted to characterize the cost of electricity generation at each hour [26].

$$C_g\left(\hat{L^h}\right) = a\left(\hat{L^h}\right)^2 + b\hat{L^h} + c \tag{10}$$

$$\hat{L^h} = \sum_{i=1}^{I} \hat{l_i^h} \tag{11}$$

where $\hat{l_i}$ represents the load of the ith consumer; the generation parameters a, b, c are constant and time-independent. In this work, we assume that the cost of generation is a function of the load, however, it is noted that other cost functions, tariff prices, or contracts could also be adopted in the proposed framework.

The retailer seeks to maximize its revenue by providing diverse types of price schemes in the DA market. Based on the discussion above, the retailer's DA-stage objection function is formulated as:

$$\max \ \hat{R}^{1\sim H} = \sum_{i=1}^{I}\sum_{h=1}^{H} \hat{l_i^h} \cdot \hat{p_i^h} - \sum_{h=1}^{H} C_g\left(\hat{L^h}\right) \tag{12}$$

$$\text{s.t.} \ \ (1) - (10) \tag{13}$$

The first term represents the monetary income received from all I consumers. The second term is defined to represent the cost of serving the aggregated load $\hat{L}$ to all I consumers.

B. RTP Design

The balance between the supply and demand is completed in the RT stage with the connection with the utility grid, which means the retailer has to trade with the utility grid to buy (or sell) its shortage (or excess) energy $\Delta\tilde{L}^h$ at the rate of utility tariff p_{Uti} (or feed-in-tariff p_{Fit}) in each hour. After determining the DA schedules of generation $\hat{L^h}$, the retailer also needs to balance the supply and demand when a discrepancy occurs in the RT stage. The cost of balancing $C_b(\Delta\tilde{L}^h)$ is:

$$C_b\left(\Delta\tilde{L}^h\right) = p_{Uti}^h \cdot \max\left(\Delta\tilde{L^h}, 0\right) + p_{Fit}^h \cdot \min\left(\Delta\tilde{L^h}, 0\right) \tag{14}$$

$$\Delta\tilde{L^h} = \sum_{i=1}^{I} \tilde{l_i^h} - \sum_{i=1}^{I} \hat{l_i^h} \tag{15}$$

where a positive $\Delta\tilde{L^h}$ denotes the retailer has to purchase power, and a negative value denotes selling.

At the trading outcome of each time slot h, the actual load demand of consumer i may be different from its expectation due to the RT deviation ($\tilde{\delta_i^h} = \tilde{l_i^h} - \hat{l_i^h}$). To avoid the price risk imposed on both the retailer and customers and mitigate the deviation, an additional constraint regarding RTP is applied:

$$\tilde{l_i^h} \cdot \tilde{p_i^h} \leq \hat{l_i^h} \cdot \hat{p_i^h} + p_{Uti}^h \cdot \max\left(\tilde{\delta_i^h}, 0\right) + p_{Fit}^h \cdot \min\left(\tilde{\delta_i^h}, 0\right) \tag{16}$$

The term $(p_{Uti}^h \cdot \max(\tilde{\delta_i^h}, 0) + p_{Fit}^h \cdot \min(\tilde{\delta_i^h}, 0))$ is the maximum monetary penalty imposed on customers based on the amount of deviation $\tilde{\delta_i^h}$. For example, if the RT load ($\tilde{l_i^h}$) exceeds the DA load ($\hat{p_i^h}$), then the maximum penalty on the deviation is $p_{Uti}^h \cdot \max(\tilde{\delta_i^h}, 0)$, which is the cost of purchasing this amount directly from the utility grid. Similarly, if the RT load is lower than the DA load, the maximum penalty is the cost of feeding the deviation back into the utility grid. The right side of Eq. (16) constrains the maximum cost that the customers should endure. This inequality constraint emphasizes that the cost of the RTP should not exceed the cost of DA-ToU plus the penalty of RT deviation, which mitigates the risk of the RTP. If there is no deviation in the RT stage, then $\tilde{p_i} \leq \hat{p_i}$, which means the RTP has to be no higher than the ToU price.

The final RTP is determined based on each customer's individual contribution. More specifically, to determine the final RTP for each customer, we can divide the customers' RT strategies into two categories based on their contributions to

the supply/demand balancing, measured by *positive* or *negative*, to calculate the penalty. The penalty charge is the utility price p_{Uti} (or the feed-in-tariff p_{Fit}), because the aggregated deviation between DA and RT (ΔL) has to be balanced with the utility grid.

- *Positive* contribution: If $\Delta L > 0$, the retailer has to purchase energy from the external grid. In this case, less consumption is encouraged and customers who have higher flexibility in reducing consumption will be given a lower price rather than being punished. Similarly, in the $\Delta L < 0$ case, increasing consumption is encouraged and customers with higher flexibility in consuming more energy are given a lower rate. However, the updated rate should locate in the aforementioned acceptable RTP range to ensure the retailer's benefit.
- *Negative* contribution: In contrast to the positive contribution case, if $\Delta L > 0$, less consumption is encouraged and customers who consumes more than the scheduled load will be punished for the violation; similarly, if $\Delta L < 0$, customers with less consumption will also be punished. The updated rate should also locate in the aforementioned acceptable RTP range.

The retailer's revenue function in the RT stage is given by:

$$\max \quad \tilde{R^h} = \sum_{i=1}^{I} \tilde{l_i^h} \cdot \tilde{p_i^h} - \left(C_g\left(\hat{L^h}\right) + C_b\left(\Delta \tilde{L^h}\right)\right) \quad (17)$$

The constraints and solution of Eq. (17) will be introduced in Section V.

IV. Consumers' Consumption Model

A. Consumers' Consumption Model

In a price-based DR program, consumers are likely to reduce their electricity consumption during high-price hours and increase their consumption during low-price hours, and consumers' consumption preferences at different hours largely depend on their daily routines and appliance types. Normally residential loads can be separated into non-responsive (e.g., lighting, refrigeration, kitchen appliances, etc.) and responsive parts (e.g., dishwasher, water heater, laundry, etc.) [27], [28], more details will be introduced in Section VI-A.

1) Non-Responsive Fix Load: The non-responsive fix load (*fl*) represents those appliances that are not able to participate in DR. A non-responsive load set of the consumer i is defined as: $\mathbf{fl_i} = [fl_i^1, fl_i^2, \ldots, fl_i^H]$, where H is the total time length.

2) Responsive Shiftable Load: The responsive shiftable load (*sl*) represents the part of electricity consumption that can be shifted according to electricity prices and consumers' preferences. A responsive shiftable load set of the consumer i is defined as: $\mathbf{sl_i} = [sl_i^1, sl_i^2, \ldots, sl_i^H]$, with the following constraints.

$$\begin{cases} sl_i^h \in \left[sl_{min}^h, sl_{max}^h\right], & h \in \left[O_i^h = 1\right] \\ sl_i^h = 0, & h \in \left[O_i^h = 0\right] \end{cases} \quad (18)$$

where $[sl_{min}^h, sl_{max}^h]$ is the range of consumer i's electricity consumption, which can be extracted from historical usage. The parameter O_i^h indicates the occupancy status, where 1 indicates an occupied household and 0 represents a vacant household. The consumer i's aggregated load is represented as:

$$\mathbf{l_i} = \mathbf{fl_i} + \mathbf{sl_i} \quad (19)$$

The consumers aim to find the best consumption of the responsive flexible load across a finite time horizon H (i.e., 24 h) to minimize the daily cost or to achieve the maximum satisfaction level. The consumption behavior of end users in this work is formulated as a utility function instead of a conventional cost function of energy purchase, which has been widely adopted in [11], [29], [30]. The utility function is divided into two parts: the utility from consuming energy and the cost of procurement. The consumer i's objective function at time h is formulated as:

$$\max \quad U_i^h = k_i^h \ln\left(1 + l_i^h\right) - l_i^h \cdot p_i^h \quad (20)$$

In (20), $k_i \ln(1 + l_i)$ is the utility achieved by the consumer i through consuming energy l_i, and p_i is the electricity price at this time. The logarithm $\ln(\bullet)$ function has been widely used in economics for modeling the preference of users, and also recently been shown to be suitable for describing the utility of power consumers, since it is closely related to proportionally fair DR. And $(1 + x)$ is a typical modified form to avoid the undesired utility of $-\infty$. Note that k_i^h is the combination of the utility weight coefficient and the consumption preference parameter. It is derived from Eq. (20) that a greater value of k indicates that the user is willing to consume more to improve satisfaction. By combining Eqs. (2), (3), and (20), it is found that the only difference between $\mathbf{U_i}(\hat{p}_i)$ and $\mathbf{U_i}(p_0)$ is the value of p, while other parameters (i.e., k_i and l_i) are the same. Thus to ensure the consumers' willingness of participating in the newly designed pricing schemes, the electricity cost under the new rate should be no higher than the previous ones.

$$\sum_{h=1}^{H=24} l_i^h \cdot \hat{p_i^h} \leq \sum_{h=1}^{H=24} l_i^h \cdot p_0^h \quad (21)$$

For any given price p_i, the consumer i adapts its consumption to the best response as l_i^* for maximizing its utility U_i:

$$l_i^* = \arg\max \quad U_i(l_i, p_i) \quad (22)$$

To solve Eq. (22), we note that the parameter l_i^*, at which the consumer i achieves its maximum utility in response to a price p_i^*, can be found from Eq. (20),

$$l_i^* = k_i/p_i - 1 \quad (23)$$

This optimal solution holds when the value locates in the consumption range constraints by Eqs. (1), (2), (3), and (16). Otherwise, the optimal solution l_i^* is always obtained on the boundary due to its strict concavity.

B. Non-Intrusive Load Monitoring and Occupancy Inference

Fig. 1 illustrates how Non-Intrusive Load Monitoring (NILM) system might work in practice with an example of a 1Hz residential load profile for a 24-h period in the Electricity Consumption and Occupancy (ECO) dataset.[1] The power use

[1] https://www.vs.inf.ethz.ch/res/show.html?what=eco-data

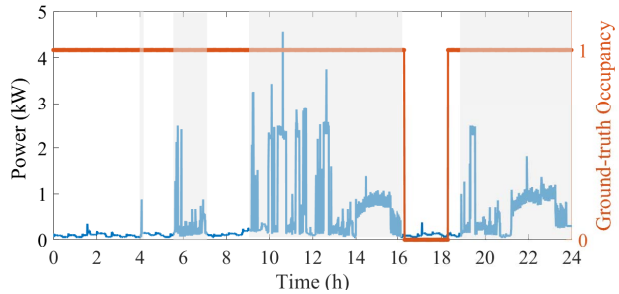

Fig. 1. The relationship between high-frequency (1Hz) load consumption and ground-truth occupancy status of a household. Active periods are illustrated by shaded areas.

is continually monitored and then the occupancy status and active periods are determined. Note that the ground-truth label does not necessarily imply there is a full DR opportunity (e.g., midnight time). A decision will be made as to whether there is likely to be a probability of DR (PDR, see Eq. (29)) of this consumer based on historical patterns of occupancy and energy consumption.

If the ground-truth occupancy information can be collected and used as a training dataset, supervised learning can be applied for occupancy detection. However, in practice, there are situations where the training data is challenging to obtain, e.g., without consumers' collaboration due to privacy concerns. Then NILM could offer an alternative solution to address this challenge. For example, an unsupervised NILM approach could be leveraged, which purely relies on the load data without occupancy labels [31]. By disaggregating the collected data stream into individual load signatures and matching each signature with reference signatures stored in a database, the NILM approach is able to extract the responsive shiftable loads and then determines the house's occupancy status. In this work, we adopt a similar NILM approach with [31], [32]. The whole time interval (e.g., one day) is first evenly divided into smaller time windows τ, and the aggregated load of the consumer i is denoted as: $\mathbf{l_i} = [l_i^1, l_i^2, \ldots, l_i^\tau]$, where the tth ($t \in [1, \tau]$) element denotes the aggregated load at time t. Then two metrics are defined to infer the occupancy status:

- Average power $\mathbf{N}_{ave}$: By detecting changes in the average power $\mathbf{N}_{ave}$ over a time window τ, a house is considered to be occupied ($O = 1$) at time t if the $\mathbf{N}_{ave}$ exceeds a predefined threshold.
- Power range $\mathbf{N}_{mm}$: The power range $\mathbf{N}_{mm}$ is defined as the difference between the absolute minimum and absolute maximum power, and a house is considered to be occupied ($O = 1$) at time t if $\mathbf{N}_{mm}$ exceeds a predefined threshold.

The hypothesis from [31], [32] is that an house in an occupied period generally implies a higher $\mathbf{N}_{ave}$ and a wider $\mathbf{N}_{mm}$ compared to a vacant status due to consumers' activities. Intuitively, the correlation between average power $\mathbf{N}_{ave}$ and occupancy status O is due to customers' interaction with responsive appliances, which increases the household's aggregated power. Besides, some interactions may increase the power range $\mathbf{N}_{mm}$ however without increasing the average power $\mathbf{N}_{ave}$. By utilizing this NILM method, the retailer is able to establish a proxy for ground-truth occupancy information. Then this inferred occupancy can be used for future DR program design and analysis. However, occupied time periods do not necessarily imply that the consumers are willing to shift their load, it still depends on the consumers' daily routines and historical consumption range, which is defined in Eq. (18).

V. Stackelberg Game-Based RTP Design

We consider the RTP design problem (Θ) as a one-N interaction in which there is one retailer as a leader and N consumers as followers. The retailer determines the RTPs ($\mathbf{P}$) that achieve its optimal profits (upper-level problem), while the consumers adjust their flexible consumption ($\mathbf{L}$) according to their received RTP signals (lower-level problem). The retailer is a price-maker who can change the price without losing consumers as long as the RTPs do not reduce consumers' utilities by following incentive compatible. Besides, the retailer design penalty rules to hedge against significant load variation in RT. The consumers are assumed to operate according to the principle of utility maximization (20). Then the game (Θ) is formulated as follows (please note the time superscript h is omitted in this section).

$$\Theta = \{R, \{\mathbf{P}\}, \{\mathbf{U}\}, \{\mathbf{L}\}\} \tag{24}$$

The first term R refers to the retailer's revenue function, as defined in Eq. (17); $\{\mathbf{P}\}$ is the retailer's price design strategies set, which is constrained in Eqs. (1), (2), and (16); the third term $\{\mathbf{U}\}$ is the utility functions set of all consumers, as defined in Eq. (20); $\{\mathbf{L}\}$ is the consumers' consumption strategies set, which are constrained in Eq. (18).

Let's denote l_i^* to be the best-response strategy of consumer i by solving Eq. (20), and $\mathbf{L}^*$ to be the best strategies set of all consumers in each time slot h, i.e., $\mathbf{L}^* = [l_1^*, l_2^*, \ldots, l_I^*]$. Then the Stackelberg Equilibrium (SE) of the proposed game can be defined as $(\mathbf{L}^*, \mathbf{P}^*)$, if and only if the following inequalities hold:

$$R(\mathbf{L}^*, \mathbf{P}^*) \geq R(\mathbf{L}^*, \mathbf{P}) \tag{25}$$

$$U_i(\mathbf{L}^*, \mathbf{P}^*) \geq U_i(l_i, \mathbf{L}_{-i}^*, \mathbf{P}^*) \tag{26}$$

where $\mathbf{L}_{-i}^*$ denotes the best load consumption set of all consumers except i. Eqs. (25) and (26) emphasize that the final strategies set of the retailer and consumers, i.e., $(\mathbf{L}^*, \mathbf{P}^*)$, yield the maximum revenue of the retailer's, and maximum utilities of the consumers'. By substituting (25) and (26) into (17) and (20), respectively, we have:

$$(\mathbf{L}^*, \mathbf{P}^*) = \arg\max \; R(\mathbf{L}^*, \mathbf{P}) \tag{27}$$

$$\text{s.t.} \;\; l_i^* = \arg\max \;\; U_i(l_i, L_{-i}, \mathbf{P}) \tag{28}$$

Consider the game Θ defined in (24), the set of strategies $(\mathbf{L}^*, \mathbf{P}^*)$ constitutes an SE of the game. We propose to follow the theorem in [17] that proves there exists a unique SE.

Theorem: For the proposed one-N Stackelberg game (Θ), there exists a unique SE if the following conditions are satisfied.

1) The strategy set of each player is nonempty, convex and compact.

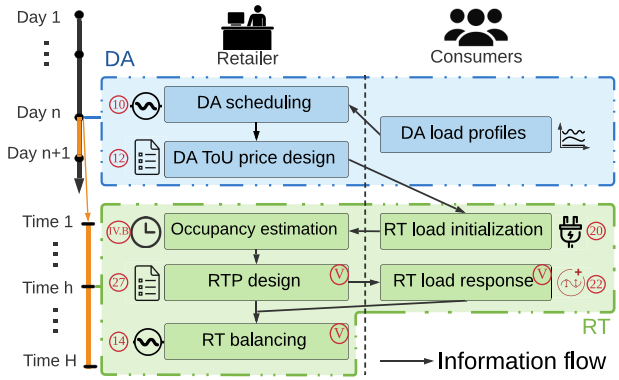

Fig. 2. Interaction between the retailer and consumers.

2) Each follower has a unique best response strategy once given the leader's strategy.
3) Leader also has a unique optimal strategy once given the identified best strategies of all followers.

Proof: First, we notice that the strategies set $\{\mathbf{L}, \mathbf{P}\}$ of the consumers and retailer are non-empty and defined by convex constraints, thus these sets are readily nonempty, convex, and compact, and there will always exist non-empty solutions. Second, for the consumers, the utility function U_i is strictly concave with respect to l_i once p_i is given, hence for any price within the range constrained by Eqs. (1), (2), (3), and (16), each agent will have a unique best strategy l_i^* for maximizing its utility U_i. Third, to prove condition 3, we first substitute (23) into (17), then we can rewrite the (17) as a function only containing variables p_i, and each variable is independent with each other. Then we can get the Hessian matrix and find it's a negative definite matrix. A detailed proof is provided in **Appendix**. Thus, the game Θ is able to continue until convergence to reach a SE.

Fig. 2 depicts the conceptual framework of the two-stage interaction between the retailer and consumers by connecting the components and models in Sections III–V. The y-axis indicates the decision-making process from the DA stage to the RT stage. The vertical dashed line separates the decision-making of the retailer and customers. The DA stage is illustrated in the blue box and the RT stage is in the green box. DA stage decision-making occurs at the beginning of the operation day n, while the RT decision covers the time slots from 1 to H in day n. The circled red Arabic and Roman numerals indicate the equations and sections, respectively. The arrows indicate the information flow directions. ■

VI. Dataset Summary

A. Basic Data Information

The ECO dataset collects data from 6 households in Switzerland, which contains: i) 1 Hz aggregated consumption data, ii) 1 Hz plug-level data measured from selected appliances, and iii) occupancy information (exclude household 6, thus we only use 5 households in this work). Fig. 3 shows a boxplot of power consumption and its relationship with historical average occupancy of five occupancy-labeled consumers

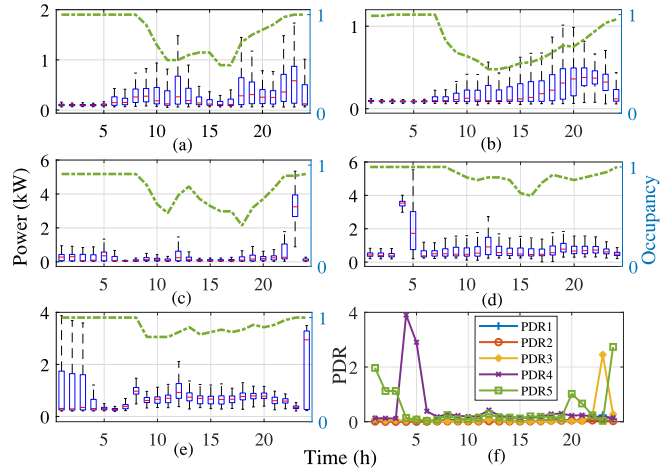

Fig. 3. The relationship between the historical load consumption (outliers are deleted in the boxplot) and the average ground-truth occupancy status throughout the dataset (a)-(e). The x-axis shows the hour of the day, the left y-axis denotes the historical power consumption, and the right y-axis denotes the average ground-truth occupancy status over the same period in the dataset. The PDR of consumers is illustrated in (f).

TABLE I
Summary of Major Responsive Appliances

Appliance	*House*	*Energy Ratio*	*Time*
Washing machine	1	8.47%	5 a.m. - 10 p.m.
Dryer	1	8.08%	9 a.m. - 2 a.m.$^{+1}$
Laptop	2	3.50%	9 a.m. - 1 a.m.$^{+1}$
Dishwasher	2	7.62%	7 a.m. - 1 a.m.$^{+1}$

throughout the ECO dataset. The boxplot displays the historical consumption data based on a five number summary (minimum, first quartile (Q1), median, third quartile (Q3), and maximum). It is seen that each consumer has a different daily routine and peak load hours, which constitutes the main motivation of our work.

The detailed monthly electricity consumption of each appliance covered by the smart plugs can be found on the website of the ECO dataset and [33]. Table I only lists four major shiftable appliances collected from households 1 and 2, since there are limited data available for households 3-5. The *Energy Ratio* indicates the consumption proportion of this appliance in a month, and *Time* shows the historical operation time of this appliance. Due to the data availability, we assume all 5 residential customers have a similar appliances components and a same proportion (30%) of responsive demand in this work, since we focus on the effectiveness of customized prices design. The reason why we choose 30% is that the consumption (kWh) of these four flexible appliances in households 1 & 2 consist of 27.7% of the monthly consumption.

B. Probability of Demand Response

According to [34], customers of greater variability and higher consumption are suitable for price-based demand response programs for their flexibility to modify their consumption. To further describe the relationship between the consumption flexibility together with the occupancy status over a *long-term* period, the concept of probability of demand

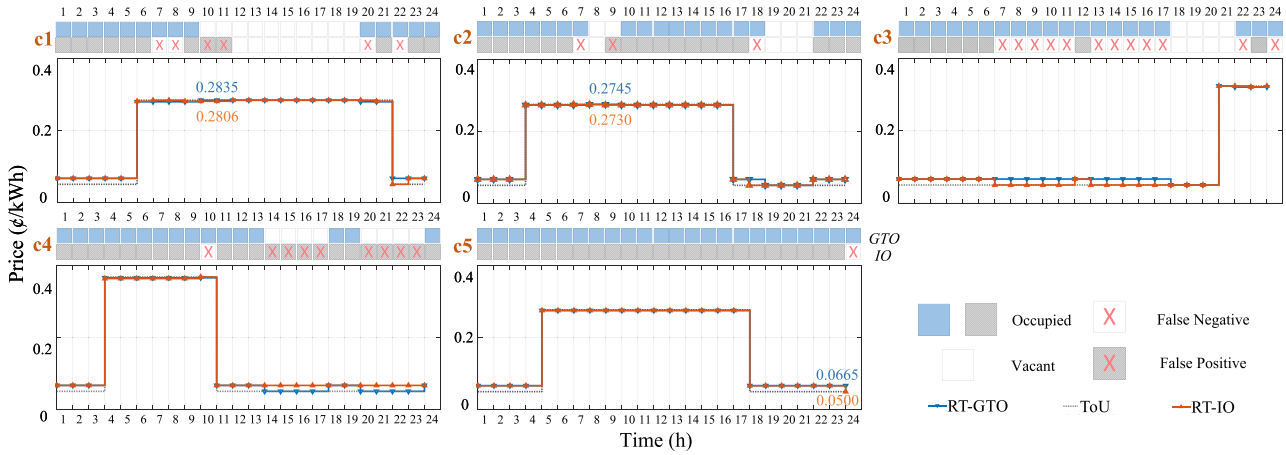

Fig. 4. The ToU/RTP pricing schemes and GTO/IO for 5 consumers (c1-c5). The x-axis represents the time, and y-axis represents the designed price. The squares on the top of each subfigure indicate the occupancy status: filled squares refer to occupied and blank squares refer to vacant houses. The first row represents GTO, and the second row represents IO. The false occupancy inferences are marked with red ×. The price designs in the RT-GTO and RT-IO cases are represented as blue and red lines, respectively. The DA ToU price is illustrated as grey dashed lines.

response (PDR) is proposed in [35], which is defined as:

$$PDR = \frac{\bar{l} \times \sigma_l \times \bar{o}}{1 + \sigma_o} \tag{29}$$

where $\bar{l}$ and $\bar{o}$ are the mean consumption and occupancy status over the dataset, respectively, and $\sigma(\cdot)$ is the standard deviation. Overall, a household with higher consumption ($\bar{l}$), greater variability (σ_l), and being occupied during a given period ($\bar{o}$), tends to have a higher PDR. On the other side, a large variation in the occupancy status (i.e., σ_o), combined with a small variation in the load consumption (i.e., σ_l), suggests a lower PDR. The PDR for all consumers is illustrated in Fig. 3(f). The estimated PDR value from Eq. (29) requires further validation to show its effectiveness in practice, which could be evaluated by measuring household load response over a longer period.

When it comes to the PDR on a *short-term* period, such as an operation day, the customers are aware of their ground-truth occupancy data, which is a binary value (either 1 or 0). Thus we assume a zero threshold in our work, which means there only exists a positive PDR when the household is occupied ($O = 1$), otherwise the PDR is zero ($O = 0$). And this zero threshold is also in accordance with the occupancy-based DR model in Eq. (18).

C. Experimental Set-Up

As discussed in [36], sharing someone's real-time high-frequency consumption data in addition to their occupancy status will inevitably create or exacerbate issues of privacy and security. For example, high-frequency energy consumption data could be used to better (i) estimate private patterns, such as the amount of time that one consumer spends on specific appliances, and (ii) infer whether the household is occupied or not. To streamline the model and avoid necessary privacy concerns, the following assumptions are made in this study:

i) A flat utility rate of 0.2 \$/kWh is used as the initial value in the case study, which is a price close to the realistic Switzerland market price (0.21 CHF/kWh) [37]. The feed-in-tariff is chosen as 0.04 \$/kWh, which is lower than the minimum customized price (0.05 \$/kWh) to ensure the consumers' benefits. Note that time-varying prices could also be used to establish the model.

ii) Due to limited availability of load dataset containing occupancy status, consumers are assumed to have adopted their original consumption preference as the best response to the initial flat price in this work. If the load dataset under time-varying prices is available, a more accurate model could be leveraged to estimate the consumers' consumption preferences.

iii) The time resolution of the dataset is set to be 1 hour to protect consumers' privacy, which also matches the ToU pricing interval of most existing electricity markets.

VII. Case Study

To evaluate the effectiveness of the proposed method, the load and occupancy data of five households on July 26, 2012 is selected, and the following five scenarios are selected for comparison: (i) *baseline:* represents the original dataset without customized price deployment on the selected day, (ii) *RT-GTO:* represents a system in which the retailer has an accurate ground-truth occupancy (GTO) status with the proposed two-stage decision-making framework, and (iii) *RT-IO:* represents a system in which the retailer has the inferred occupancy (IO) of households with the proposed two-stage decision-making framework.

A. Results of Two-Stage Decision-Making

Fig. 4 shows the ToU/RTP design and GTO/IO for all consumers (c1-c5). The retailer designs different ToU prices (grey dashed lines) at the DA stage to encourage consumers to shift their responsive load to off-peak hours with lower electricity prices, thereby making the aggregated load flatter to maximize its revenue. It is seen from Fig. 3 that peak load occur at different times for each consumer, thus it's reasonable to design customized pricing schemes for consumers to fully incentivize

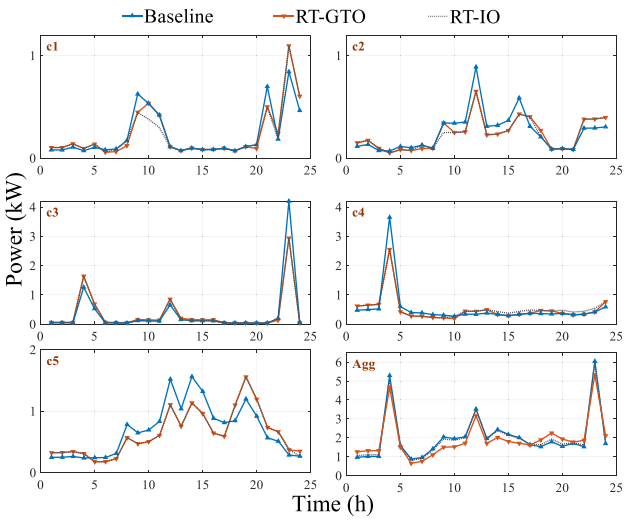

Fig. 5. The load response of 5 consumers shown as c1-c5, and the aggregated load response shown as Agg. RT-GTO refers to the load response with GTO, and GT-IO refers to the expected response with IO.

their willingness to participate in DR. Different from ToU prices that consist of several blocks, RTP (colored solid lines) has a more flexible pattern and is closely related with the occupancy status. The price discrepancy occurs when the IO is different with the GTO. When a house is vacant and cannot participate in DR, the RTP has to be no higher than ToU.

Fig. 5 shows the load response under the RT-GTO and RT-IO scenarios. The RT-IO result can be regarded as the retailer's expected response from consumers. However, this expected response may not happen due to the inaccurate occupancy inference. It is seen from Figs. 4 and 5 that consumers actively respond to the price change when they are at home. More specifically, consumers tend to shift their responsive flexible load to their off-peak hours, though the off-peak hours of each consumer may not be the same. However, an RT deviation from a consumer's submitted DA load demand may incur a penalty, and the retailer will accommodate with this deviation by setting different RTPs in a specified range to balance the supply and demand, which is defined in Eq. (16). Besides, the price regulation is also positively correlated with PDR (see Fig. 3(f)). It is observed that compared with consumers 1 and 2, consumers 3-4 have higher load levels and PDR, leading to a higher contribution to the response of the aggregated load. Thus their price gaps between on- and off-peak hours are relatively higher than other consumers, as seen in Fig. 4. As a result, the proposed pricing schemes have successfully flattened the aggregated power consumption based on customized DR signals, shown as Agg case in Fig. 5.

B. Effectiveness of Occupancy Inference

The previous subsection outlines the results of the two-stage decision-making with occupancy status. This subsection will further evaluate the effectiveness of occupancy inference on DR. In NILM, the occupancy inference accuracy is evaluated by a confusion matrix.

- True positive (TP) denotes the count that a house is actually occupied and is detected occupied. In a TP case, the retailer sends out price signals, and the customer will respond to the RTP and reschedule its load.
- True negative (TN) denotes the count that a house is actually vacant and is detected vacant. In a TN case, the retailer will expect no response abilities from the consumers and no incentive will be sent out.
- False positive (FP) denotes the count that a house is actually vacant but is detected occupied. In an FP case, the retailer will not receive the expected response from the customer in a vacant household although a customized price is sent out. This false inference case leads to a main economic loss for the retailer compared with GTO information, since it might send out a lower rate to customers, but finally does not get the expected load response.
- False negative (FN) denotes the count that a house is actually occupied but is detected vacant. In an FN case, the retailer overlooks the DR ability of the customer by incorrectly estimating a vacant status. This false inference case leads to a potential economic loss for the retailer. However, since the consumption level of FN estimation is pretty low, the potential loss is not as significant as the FP case.

TABLE II
OCCUPANCY INFERENCE ACCURACY SUMMARY (1 HOUR)

Metric	TP	TN	FP	FN	ACC(%)
Count-c1	10	8	2	4	75.00
Count-c2	17	4	1	2	87.50
Count-c3	8	4	0	12	50.00
Count-c4	15	0	8	1	62.50
Count-c5	23	0	0	1	95.83
Count-all	73	16	11	20	74.17

TABLE III
SENSITIVITY ANALYSIS OF OVERALL OCCUPANCY INFERENCE

Time resolution	TP	TN	FP	FN	ACC(%)
30 mins	150	29	18	43	74.58
15 mins	307	57	33	83	75.83
5 mins	928	170	98	244	76.25
1 min	4667	847	487	1199	76.58

The occupancy inference accuracy is summarized in Table II. Count-all represents the overall inference accuracy, and count c1-c5 indicate each of the 5 consumers with 1 hour resolution data. The overall accuracy (ACC, marked in grey) is calculated by $ACC = (TP + TN)/(TP + TN + FP + FN)$. For consumers 1 and 3, although there is a higher chance for FN, their load levels are relatively low when wrong inferences occur, indicating lower consumption willingness and PDR during these time periods. As for the FP cases, e.g., away from home while leaving the appliances turned on, this case has the lowest probability (11/120), especially on consumers 1 and 4. Similarly, their load levels are also low when FP occurs. Besides, the wrong hit of occupancy inferences could be mitigated by sending adjusted price signals to other consumers who are actually at home.

Table III shows the sensitivity analysis of occupancy inference under different time resolutions. The overall ACC of

TABLE IV
RETAILER'S REVENUE

Scenario	W/o occupancy	*RT-GTO*	*RT-IO*
Revenue ($)	5.1754	5.5070	5.3713
Growth (%)	-	6.41%	3.78%

TABLE V
AGGREGATED COST OF CONSUMERS

Scenario	*Baseline*	*RT-GTO*	*RT-IO*
Cost ($)	9.7436	7.7877	7.6547
Savings (%)	-	20.07%	21.44%

TABLE VI
UTILITIES ($) AND AVERAGE COST ($/KWH) OF CONSUMERS

	Utility ($)			Average Cost ($/kWh)		
	Baseline	*RT-GTO*	*RT-IO*	*Baseline*	*RT-GTO*	*RT-IO*
1	5.2612	5.6491	5.6639	0.2	0.1830	0.1820
2	5.7582	6.1230	6.1389	0.2	0.1790	0.1783
3	10.136	10.824	10.895	0.2	0.1672	0.1650
4	14.174	14.834	14.804	0.2	0.1666	0.1697
5	18.877	20.052	20.072	0.2	0.1752	0.1749

Note: Grey cells indicate better results for consumers, either with higher utilities or with lower average costs.

occupancy inference increases from 74.58% to 76.58%, with the increase of time resolution (note that [32] with the same inference method under 1 min resolution has a higher accuracy from 73.27% to 79.09% for one household). With available high-frequency historic patterns of occupancy and consumption, some state-of-the-art machine/deep learning methods yield better accuracy [22]. However, the data collection is another challenge, since continuously recording and storing high-resolution data is costly. Besides, it may also raise privacy issues since high-resolution data may reveal residential customers' private information.

C. Market Performance

The retailer's revenue of different scenarios is summarized in Table IV. The baseline case without (w/o) occupancy inference represents that the retailer ignores the impact of occupancy status on the price design and assumes the customer has DR ability all the time. It is observed that the *RT-GTO* and *RT-IO* scenarios have increased the retailer's revenue by 6.41% and 3.78%, respectively, compared with the baseline. With a 74% occupancy detection accuracy in the *RT-IO* case, the retailer is still able to detect the best time periods with higher PDR and then design customized DR signals, and the revenue increase is slightly less than that in the *RT-GTO* case that has a 100% occupancy detection accuracy.

Table V compares the aggregated cost of all consumers under different scenarios. Customized price-based DR reduces the aggregated cost by 20% compared with the baseline flat rate. The RT-GTO case yields higher cost compared with the RT-IO case, indicating a slight economic loss for consumers if their GTO status is available to the retailer. Table VI summarizes the 5 consumers' utilities and costs under different scenarios. The individual cost is measured by the average cost, which is calculated by the total cost of an individual consumer divided by its total consumption. The grey color highlights the better results by comparing cases *RT-GTO* with *RT-IO*. In Table VI, all consumers except 4 are seen to have higher utilities or lower average costs when their GTO status is not fully monitored by the retailer, indicating the necessity of preserving private information. Consumer 4 contributes most of the aggregated peak load demand in the early morning (around 4 a.m., as seen in Fig. 5(c4)), the retailer sets a higher price for the consumer at this period. Besides, there is a higher chance of FP for consumer 4, its demand response flexibility is overlooked by the retailer. However, the utilities of all consumers are still higher than those of the baseline, which means the proposed pricing scheme is still beneficial customers. By comparing Tables IV and VI, it is seen that monitoring the full occupancy status (with the 100% accuracy of GTO) will benefit the retailer more, while the inaccurate occupancy inference case will benefit the customers more.

TABLE VII
COMPUTATION TIME WITH DIFFERENT NUMBERS OF CONSUMERS

Number of consumers	5	25	50	100	200	500
Computation time (s)	0.41	0.47	0.50	1.66	1.87	32.42

D. Scalability and Applicability Analysis

Our simulations were executed on a laptop with an Intel Core i7-6600U 2.8GHz CPU and 16.0 GB RAM. The DA ToU pricing design problem (i.e., MILP) is implemented in MATLAB2017b and programmed using YALMIP with the solver *INTLINPROG*, and it takes 53.6 seconds to obtain the optimal solution, which is acceptable in a DA market. Since DA ToU only provides a basic DR incentive to consumers, while the RTP is the final signal to determine the DR schedule, a small number of ToU schemes could reduce the complexity caused by the increasing number of consumers.

At the RT stage, the model works in a centralized manner and each consumer only needs to submit the load response to the retailer based on the RTP. To analyze the scalability and applicability of the proposed method, additional case studies are conducted by increasing the number of consumers. Extra consumers' load data is generated based on the existing dataset by multiplying a random factor from 0.5 to 1.5 due to the limited data availability. The computation cost is summarized in Table VII. Even with 500 consumers, the computation cost of RTP in each hour is only 32 seconds, which is acceptable in the RT market operation. To extend the proposed framework to a large market consisting of thousands of consumers, clustering methods could be leveraged to group the consumers with similar preferences, which has been explored in [14].

Regarding the applicability of the proposed framework, this study has shown an example and provided insights to extend the NILM method to real-world smart meter data without occupancy labels. NILM has mainly addressed two challenges for occupancy detection: (i) labelled occupancy data is challenging to collect, since it requires sensor deployment and intrusive monitoring, and (ii) the intrusive monitoring technique will lead to privacy concerns. Our results have shown

that though with a 74% accuracy with 1 hour resolution data, the NILM method is able to capture the best DR time periods, which is sufficient for occupancy-informed price design. One limitation of this study is that the ECO dataset only contains incomplete plug-in data for each consumer, and important consumption information on some responsive appliances is absent. Thus we didn't model our DR problem as an appliances scheduling problem. This gap could be bridged by using label discovery techniques or other datasets with complete plug-in data.

VIII. Conclusion

This paper proposed an occupancy-informed customized price design scheme to address challenges in energy trading and demand response in a retail market that is composed of retailer and consumers. A two-stage decision-making strategy was developed to maximize the retailer's revenue while maintaining the customers benefits. The first stage solved a mixed-integer linear programming-based day-ahead ToU pricing problem, and the second stage solved a real-time demand response problem formulated by a one-lead-N-follower Stackelberg game. In addition, the impact of household occupancy on demand response was also explored, and two types of occupancy labels were analysed, i.e., the ground-truth occupancy and the occupancy inferred using non-intrusive load monitoring. The case study demonstrated the effectiveness of the proposed two-stage pricing scheme in peak shaving and valley filling, as well as increasing both the retailer's revenue and consumers' revenue and utilities. Our results also showed that a better estimation of consumers' occupancy status is helpful to increase the retailer's profitability.

Potential future work will further explore (i) more accurate and realistic demand response models when detailed parameters of plug-in appliances are available, (ii) methodologies with more accurate non-intrusive load monitoring to further enhance the market efficiency, iii) other involved entities, such as distributed energy resources owners, energy storage and PV prosumers, and iv) other market schemes and pricing methods, such as Nash game- and cooperative game-based energy trading.

Appendix
Proof of the Stackelberg Equilibrium

For the retailer, we substitute the consumers' best response (22) into the revenue function, then Eq. (17) can be rewritten as follows:

$$\tilde{R} = \sum_{i=1}^{I} \tilde{l}_i^* \cdot \tilde{p}_i - C_g\left(\hat{L}\right) + C_b\left(\Delta\tilde{L}\right) \tag{30}$$

$$= \sum_{i=1}^{I} (k_i/\tilde{p}_i - 1) \cdot \tilde{p}_i - \left(C_g\left(\hat{L}\right) + C_b\left(\sum_{i=1}^{I}(k_i/\tilde{p}_i - 1) - \hat{L}\right)\right) \tag{31}$$

Note that only $l_i^* = k_i/\tilde{p}_i - 1$ is considered in the proof process, i.e., the scenario when optimal solution l_i^* locates on the boundary are omitted, because when this occurs, those consumers have reached their DR limit, and their DR schedules are constant numbers. $\hat{L}$ is the DA aggregated load schedule, which is a fixed value in the RT stage. We next consider if $\sum_{i=1}^{I}(k_i/\tilde{p}_i - 1) - \hat{L} > 0$,

$$\tilde{R} = \sum_{i=1}^{I} (k_i/\tilde{p}_i - 1) \cdot \tilde{p}_i - \left(C_g\left(\hat{L}\right) + p_{Uti} \times \left(\sum_{i=1}^{I}(k_i/\tilde{p}_i - 1) - \hat{L}\right)\right) \tag{32}$$

Then we see that (32) is a function containing only $\tilde{p}_i$. For simplicity, we rewrite (32) as R' by only keeping $\tilde{p}_i$-relevant terms:

$$R'\left(\tilde{\mathbf{P}}\right) = \sum_{i=1}^{I} (k_i/\tilde{p}_i - 1) \cdot \tilde{p}_i - p_{Uti} \cdot \left(\sum_{i=1}^{I}(k_i/\tilde{p}_i)\right) \tag{33}$$

Therefore the Hessian matrix of R' is given by

$$\mathbf{H} = \begin{vmatrix} \frac{\partial^2 R'}{\partial\tilde{p_1}\partial\tilde{p_1}} & 0 & \cdots & 0 \\ 0 & \frac{\partial^2 R'}{\partial\tilde{p_2}\partial\tilde{p_2}} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \frac{\partial^2 R'}{\partial\tilde{p_I}\partial\tilde{p_I}} \end{vmatrix}$$

Since each diagonal element holds a same format:

$$\frac{\partial^2 R'}{\partial\tilde{p}_i\partial\tilde{p}_i} = \frac{-2p_{Uti}k_i}{\tilde{p}_i^{\,3}} \tag{34}$$

It's seen that the Hessian matrix is a negative definite matrix, so there exists an optimal value to maximize R'.

The proof of case $\sum_{i=1}^{I}(k_i/\tilde{p}_i - 1) - L < 0$ is similar. Therefore there exists a unique SE in the proposed game and ***Theorem*** is proved.

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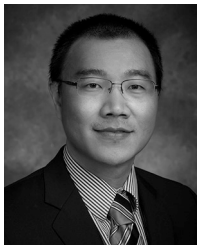

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