Customized Retail Pricing Scheme Design with a Hybrid Data-driven Method

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***Abstract*—Rapid growth of smart metering data in smart grids provides great opportunities for the retailer to design customized price schemes and demand side management (DSM) programs for different customer groups. This paper proposes a hybrid data-driven method of clustering customers' daily load profiles and optimizing different electricity retail plan recommendations for electricity retailers. By combing the user-side information with the risk-aware decision-making framework, specifically using conditional value-at-risk (CVaR) modeling method, the retailer could guarantee its accumulated revenue without doing any harm to the customers' benefit, while guiding their energy consumption behavior instead. Through large-scale experiments, it is observed that a slight increase in the customers' possible payment would be compensated by their big gain in more demand response opportunities. The retailers' profit could also be increased by roughly 49%-51% and 33%-38% with or without enabling demand response programs.**

***Index Terms*—automatic meter reading, dynamic pricing, electricity retail market**

I. Introduction

Smart grids have been revolutionizing power generation, transmission and distribution through multiple types of two-way flow of energy and information. As an important information source coming out of the demand side, automatic meter reading (AMR) has gained increasing popularity worldwide. For example, in Nordic countries, the Finnish government passed an act, which stated that at least 80% of the customers of each distribution system operator (DSO) must have a smart meter by December 2013, and nowadays in 2021 almost every customer (extremely close to 100%) in Finland is equipped with a smart meter [1]. Driven by the requirement of grid operation transparency and full capture of carbon trajectory, this kind of phenomena could also be observed in many other countries, such as Germany, United States, Germany and China [2] [3]. The abundant data set of electricity consumption of residential customers enables accurate load profiling and data analytic application [4] [5], by which both the electricity wholesale market and retail market can have market-driven advanced technology development [6] [7].

Usually, the load profiles refer to electricity consumption behaviors of customers over a specific period, e.g., one day, and can help retailers in electricity market understand how electricity is actually used by different customers and obtain the load patterns to provide better customized services. For example, abundant AMR data provides great opportunities for the retailer to design customized price schemes and demand side management (DSM) programs for different customer groups [8] [9]. For example, in [10], the authors carefully design different retail plans and recommend these retail plans to customers with unknown characteristics by using the information of other similar relevant customers and collaborative filtering techniques used mostly in advertising field. In [11], a similar idea is implemented again for personalized tariff scheme design in distribution networks. Some temporal customized pricing scheme called *coupon* [12] or *voucher* [13] have also been proposed to stimulate different price elasticity of different customers.

In contrast to these works and on top of our previous work [8], this paper emphasizes the trade-off between retailer's profit and customer's benefit, as well as the risk associated with the pricing scheme proposal, which is often ignored in most other analysis [14]. Specially, it introduces a hybrid data-driven method of clustering customers' daily load profiles with consequential carefully designed electricity retail plan recommender system to provide end-users the customized retail price scheme.

II. Methodology

A. Overall framework

A retailer can be seen as an intermediary between producers and consumers, which supplies energy, in a financial sense, to the customers that are not participating directly in the electricity market. DSO is responsible for the physical delivery of electricity with its own distribution network. That is why distribution tariff is separately charged in the final electricity bills. In this paper, we assume some small retailers are not supposed to own any generating units or to consume electricity [15].

In this framework and illustrated in Figure 1, it is assumed that the profit of a retailer mainly comes from the difference between the revenue of selling (supplying) electricity to customers and the cost of purchasing electricity in the wholesale electricity markets (*Elspot* and *Elbass* in Nordpool case). For

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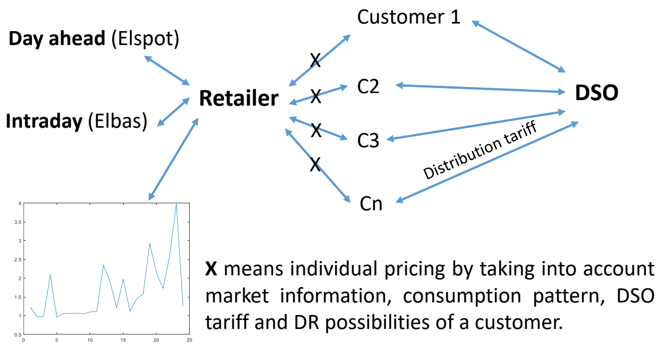


Fig. 1: Customized pricing service provided by retailer

simplification reason, the hedging and other financial tools are not considered in the problem formulation. At this moment, we mainly focus on designing a proposed customized pricing service with leveraging clustering techniques and consideration of demand response. Without loss of generality, the module of customized pricing service can be easily combined with retailers' comprehensive decision-making, including consideration of financial markets, in the future holistic retailer model.

We should note that the assumption that electricity consumption behavior of individual small customer is hard to forecast considering the household highly stochastic daily lifestyle. Most accepted or accurate forecasting are only available at the aggregation level.

B. Clustering analysis

The customized pricing scheme design in term of retailer's decision-making depends heavily on the knowledge of customers' energy consumption behavior. Thus, some clustering analysis similar to [16] is conducted to facilitate the further pricing optimization problem. In this paper, Results from a K-means clustering are used to estimate the possibility distribution of a customer's load profiles within the two year study period, which is illustrated in a pictorial example as shown in Figure 2.

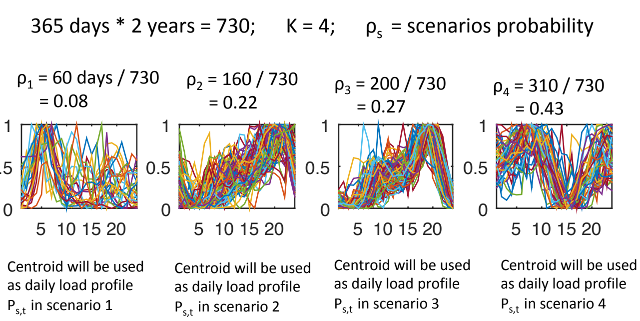


Fig. 2: Illustrative example of possibility distribution of a customer's load profile

C. Retail pricing scheme design

From the retailer's perspective, it should carefully design the individualized retail pricing scheme for each customer who subscribed to its service. Similar to many other works presented in [10] and [11], this kind of customized pricing recommendation problem can be formulated as an optimization problem (1)-(12). The risk of pushing customers towards the undesired manner is also considered. However, the retailer should also guarantee the baseline of customer benefit only with tolerance of slight deviation to the original retail plan compensated by some additional gain opportunities out of demand response (DR) programs.

The objective function (1) is to maximize the retailer's revenue under risk terms, in which ρ_s is the scenario probability, $P_{s,t}$ the energy consumption in scenario s and time interval t, r_t retail selling price, r_{da} day-ahead purchasing price; β, ξ_{var}, α and η_s are risk variables associated with CVaR calculation similar to [10]. Regarding the various constraints, (2) and (3) stands for the CVaR conditions; (4) claims the allowed cost change for customers with payment margin ϵ_{margin}; (5)-(8) states the demand response opportunities within the pricing scheme intervals, in which x_{DR} is the binary variable to indicate the acceptance of DR signal, π_{DR} the demand response incentive, r_{th} the allowed price difference threshold and E_{DR} the shifted energy consumption; In details, (5) indicate whether the difference between new price scheme and old price scheme need to trigger the DR programs; (7) and (8) reallocate the shifted energy consumption to DR period and non-DR period, respectively; T_b and T_e are the available beginning time and ending time of the DR program, respectively; (9) reflects the load profile constraint after accepting the retail price scheme; (10)-(12) further restrict some necessary ancillary conditions, such as price upper and lower bounds, price comparison to other retailers and DR switch on/off conditions.

$$\begin{aligned} \max_{r_t,\xi_{var},\eta_s} \quad & \sum_{s}^{N_S}\sum_{t}^{N_T} \rho_s P_{s,t}\Delta T(r_t - r_{da}) \\ & + \beta\Big(\xi_{var} - \frac{1}{1-\alpha}\sum_{s}^{N_S}\rho_s\eta_s\Big) \end{aligned} \tag{1}$$

s.t.

$$\eta_s + \sum_{t}^{N_T} P_{s,t}\Delta T(r_t - r_{da}) - \xi_{var} \geq 0, \quad \forall s \tag{2}$$

$$\eta_s \geq 0, \quad \forall s \tag{3}$$

$$\sum_{s}^{N_S}\sum_{t}^{N_T}\rho_s P_{s,t}\Delta T \times r_t \leq \sum_{s}^{N_S}\sum_{t}^{N_T}\rho_s P_{s,t}\Delta T \times r_{t,old} + \epsilon_{margin} \tag{4}$$

$$x_{DR} \geq \frac{1}{T_e - T_b + 1}\sum_{t=T_b}^{T_e} r_t - \frac{1}{T_e - T_b + 1}\sum_{t=T_b}^{T_e} r_{t,old} - r_{th} \tag{5}$$

$$E_{DR} = \Big(\sum_{t=T_b}^{T_e} P_{s,t}\Delta T\Big) \times \pi_{DR} \times x_{DR}, \quad \forall s \tag{6}$$

$$P'_{s,t} = P_{s,t} - P_{s,t} \times \pi_{DR} \times x_{DR}, \quad \forall s, \quad t \in [T_b, T_e] \tag{7}$$

$$P'_{s,t} = P_{s,t} + \frac{E_{DR}}{(N_T - T_e + T_b - 1)\Delta T} \times x_{DR}, \quad \forall s, \quad t \in [1, T_b) \cup (T_e, N_T] \tag{8}$$

$$\sum_{t}^{N_T} P'_{s,t} \Delta T \times d_t \leq \sum_{t}^{N_T} P_{s,t} \Delta T \times d_t, \quad \forall s \tag{9}$$

$$r_{min} \leq r_t \leq r_{max}, \quad \forall t \tag{10}$$

$$\frac{1}{N_T} \sum_{t}^{N_T} r_t \leq r_{ave}^{others} \tag{11}$$

$$x_{DR} \in \{0, 1\} \tag{12}$$

III. Experimental results

In this paper, the proposed optimization problem is solved via *fmincon* MATLAB toolbox functions.The case studies use electricity consumption AMR datasets collected from a real Finnish distribution system operator in northern Europe, which includes 5,398 low voltage customers (fuse size $\leq 3 \times 63$ A) in a small region [8]. We randomly pick several commercial customers and residential customers to analyze the clustering effect on customized retail price scheme design.

A. Customized time-of-use pricing design

This case study present the result of customized time-of-use (TOU) pricing design for a particular customer, who is chosen as an example, with consideration for customer's energy consumption pattern and demand response effect. The historical daily load profiles are collected during consecutive four years from year 2010 to 2014. Then we use the day-ahead spot market price and the newly collected demand curve in 2015 to test the proposed method.

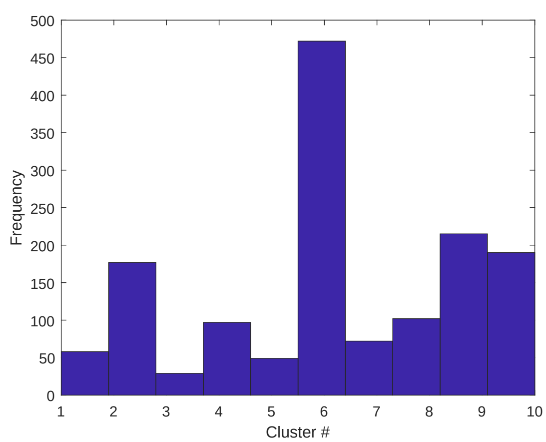


Fig. 3: Clustering results of daily load profiles of customer No. 1200

The clustering analysis of selected customer No.1200 is presented in Figure 3, as well as the associated customized TOU pricing scheme presented in Figure 4. We can observe that the new daily average TOU pricing scheme (red line) changes dramatically compared with the more stable old ones (blue line), however following the basic change trend of

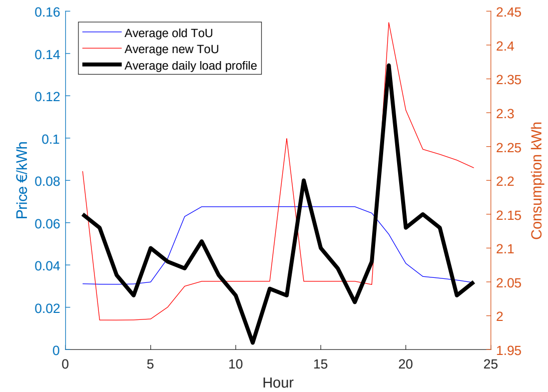


Fig. 4: Customized TOU design for customer No. 1200

daily average load profile (black line). It implies the fact that more inter-temporal pricing change during 24 hours may help stimulate the instant energy consumption behaviour change in response to the external system operation requests, such as load peak shaving. This claim will be justified and further analyzed in Section III-B.

B. Economic analysis of different customers

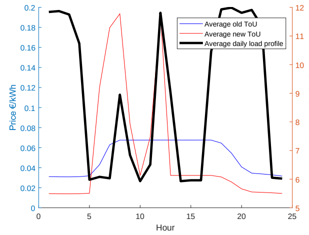
This case study applied the proposed method of customized pricing design for different type of customers and analyzes the economic effect on both the customers and the retailer. The typical TOU designs for different customers are presented in Figure 5. The statistical analysis of these customers' payment for the daily electricity fee are presented in Figure 6. It can be observed that by adopting the new price scheme, the electricity fee over the whole year would not increase or just increase slightly (compare *cusTotal* with *cusTotalOld*). Even the electricity fee could be reduced obviously (compare *cusTotalDR* with *cusTotalOld*) by participating demand response programs, explained by equation (6)-(8), enabled by such a flexible new pricing scheme.

The similar observation can also be found in Figure 7, in which the annual total electricity fees of the same four customers match with their statistical daily expense.

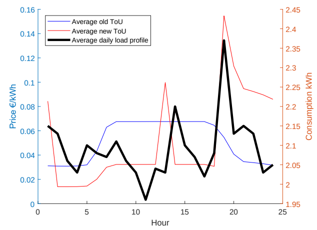
Following the similar annual calculation of the distribution tariff components (TOU), as shown in Figure 8 and retailer's overall profit, as shown in Figure 9, it can be found that the annual distribution tariff paid by different customers are almost the same (just a little bit lower) with the original price scheme. However, the retailer's annual profit collected from customers could be significantly improved due to providing customers the new price schemes. It is safe to suggest that the price component other than distribution tariff contribute a lot to this profit improvement and dominate the pricing structure. In other words, the public distribution service almost will not be affected, but the customers' subscription to different private pricing service does.

C. Large-scale experiments

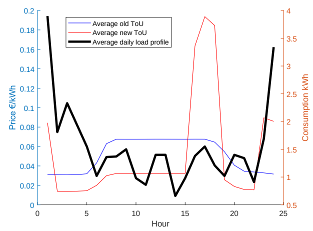
Besides the analysis of the selected four customers, namely customer No.15, No.1200, No.2800 and No.4500, we also



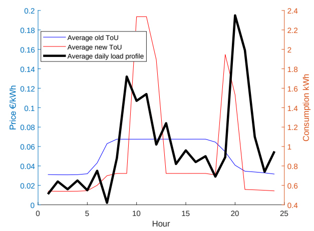
(a) Customer No.15



(b) Customer No.1200

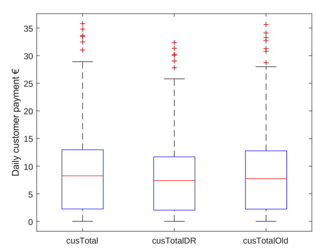


(c) Customer No.2800

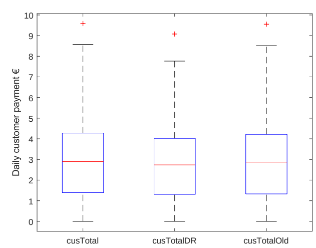


(d) Customer No.4500

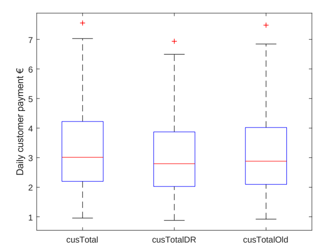
Fig. 5: Customized TOU design for different customers



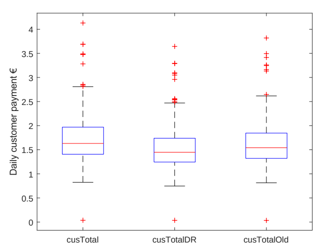
(a) Customer No.15



(b) Customer No.1200



(c) Customer No.2800



(d) Customer No.4500

Fig. 6: Daily total electricity fee of different customers with customized TOU design (cusTotal: electricity fee with new TOU; cusTotalDR: electricity fee with new TOU and DR; cusTotalOld: electricity fee with old TOU)

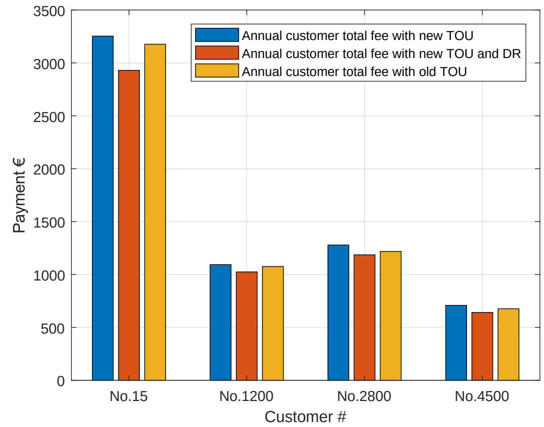


Fig. 7: Annual total electricity fee of different customers

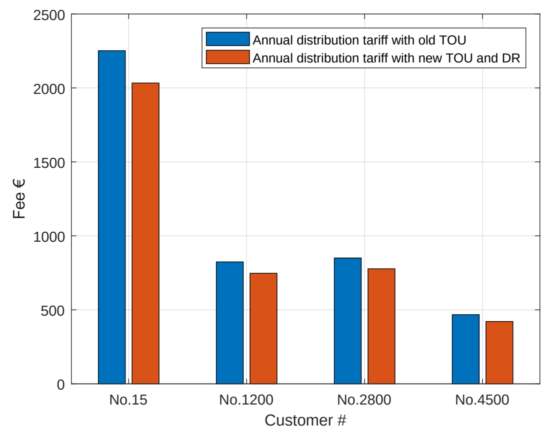


Fig. 8: Annual distribution tariff paid by different customers

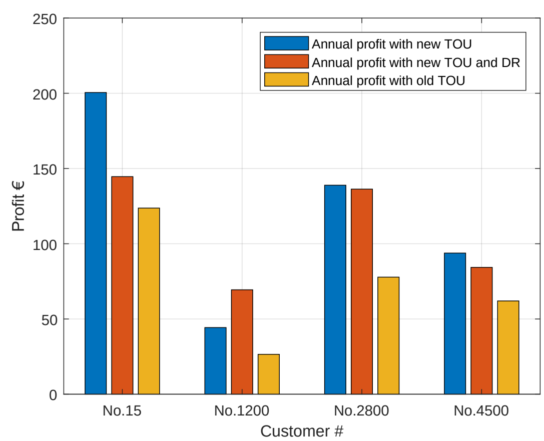


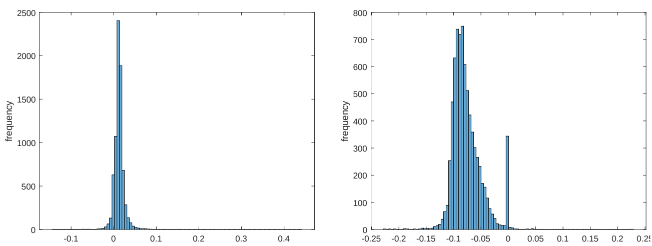
Fig. 9: The retailer's annual profit collected from different customers

conduct the similar analysis and experiments on the dataset that consists of all the 5398 customers. The value change of customers' electricity fee and retailer's profit by adopting the customized retail pricing scheme is summarized in Table I. In line with the previous analysis of specific samples, we can conclude that the customers' payment may increase slightly (about 1%) in exchange for considerable payment reduction (about -8%) with DR program opportunities.

By statistical analysis of all the 5398 customers and drawing the frequency of value change, more detailed information of group trend could be observed as a supplement to Table I. In Figure 10, the probability of customer cost reduction with DR is distributed wider around -8% than those without DR. In Figure 11, the probability of retailer's profit increase with

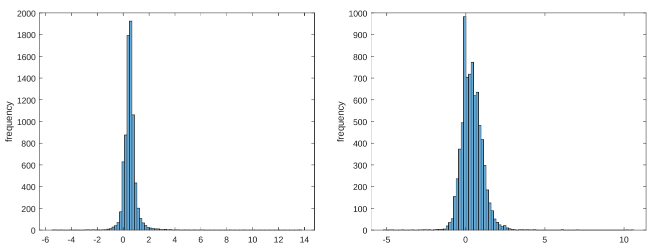
TABLE I: The value change of payment and profit affected by customized pricing

Increase (%)	**Mean**	**Median**
Customer' payment	1.28%	1.22%
Customer' payment with DR	-7.58%	-8.20%
Retailer' profit	51.77%	49.56%
Retailer' profit with DR	38.48%	33.07%



(a) Without demand response (b) With demand response

Fig. 10: The ratio of increase of customer's payment



(a) Without demand response (b) With demand response

Fig. 11: The ratio of increase of retailer's profit

DR is distributed wider around 1% than those without DR.

Last but not least, Table II summarizes the percentage of customers affected by the proposed pricing scheme design method. We can get another interesting observation that under such pricing scheme retailer may benefit more (89.47% pay more and 69.46% increase retailer's profit) than what customer could achieve (10.53% and 99.51% pay less with or without DR). However, this phenomena could be justified by the fact that retailer usually bears much more risk in the whole market bidding in addition to the retailing business.

TABLE II: The percentage of customers affected by customized pricing

Percentage (%)	**Without DR**	**With DR**
Customers that pay more	89.47%	0.49%
Customers that pay less	10.53%	99.51%
Customers that increase retailer's profit	89.47%	69.46%
Customers that decrease retailer's profit	10.53%	30.54%

IV. Conclusions

This paper proposes a hybrid data-driven method to design the customized retail price scheme for individual customers with consideration for their consumption pattern and the demand response effect. Technically, it combines a commonly used clustering method with an CVaR optimization framework of risk management to guarantee retailer's revenue. Meanwhile, this method can also benefit electric customers, while demand response opportunities are taken into account. The customers could choose to bear a slight cost increase possibility in exchange for a much more demand response incentive gain. In the future, some more comprehensive pricing components, like trading forward contracts and hedging, will be incorporated in the decision-making process, which enable designing more electricity retailing business models.

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