An Optimal Differential Pricing in Smart Grid Based on Customer Segmentation

Fanlin Meng*, Behzad Kazemtabrizi*, Xiao-Jun Zeng† and Chris Dent‡
* School of Engineering and Computing Sciences
Durham University, Durham, United Kingdom
Email: fanlin.meng@durham.ac.uk, behzad.kazemtabrizi@durham.ac.uk
† School of Computer Science
University of Manchester, Manchester, United Kingdom
Email: x.zeng@manchester.ac.uk
School of Mathematics
University of Edinburgh, Edinburgh, United Kingdom
Email: Chris.Dent@ed.ac.uk

***Abstract*—In smart grids, dynamic pricing (e.g., time-of-use pricing (ToU), real-time pricing (RTP)) has recently attracted enormous interests from both academia and industry. Although differential pricing has been widely used in retail sectors such as broadband and mobile phone services to offer 'right prices' to 'right' customers, existing research in smart grid retail pricing mainly focus on an uniform dynamic pricing (i.e. all customers are offered at the same prices). In this paper, we take the first step towards an optimal differential pricing for smart grid retail pricing based on customer segmentation. A differential pricing framework is firstly presented which consists of customer segmentation analysis, and a two-level optimal differential pricing problem between the retailer and each customer group. At the upper level, a pricing optimization problem is formulated for the retailer while at the lower-level, an optimal tariff selection problem is formulated for each customer group (e.g., price sensitive, price insensitive) to minimize their bills. By comparing with a benchmarked uniform ToU, simulation results confirmed the feasibility and effectiveness of our proposed optimal differential pricing strategy.**

I. Introduction

With the smart meter roll-out [1], dynamic pricing (e.g, real-time pricing (RTP) and time of use pricing (ToU)), which could incentivise customers to shift their peak-time usages (e.g., in the evening) to off-peak time (e.g., night), have attracted growing interests from both academia and industry [2][3][4]. For instance, [3][4] propose a two-level model for optimal real-time pricing by assuming customers' responses to prices are prefect information. An optimal dynamic pricing scheme is introduced in [5] where customers' responses are unknown to the retailer and need to be identified from smart meter data using machine learning techniques. It is worth mentioning that all the above optimal dynamic pricing approaches provide the same prices to all the customers. As different customers have different energy consumption profiles and behaviours when facing even the same dynamic price signals, conventional uniform dynamic pricing approaches might not be able to take into account all customers' characteristics. For instance, an uniform dynamic price signal might be not sufficient to incentivise price sensitive customers to shift their peak-time usages to off-peak time periods (i.e. price not high enough in peak time or low enough in off-peak time). However, the same price signal might be too overwhelming for price insensitive customers (i.e. the peak time price is too high to them and would increase their financial burdens). As a result, a differential pricing framework based on customer segmentation being able to offer different tariffs to different types of customers seems to be very promising to address the above matters existing in uniform ToU pricing.

Although differential pricing has been used in retail sectors such as broadband and mobile phone services to offer 'right' prices to 'right' customers [6] and to enhance retailers' profitability and improve customer satisfaction, it has not received deserved attention from the smart grid research community. [2] proposes an approach to designing multiple ToU tariffs for multi-types of users (e.g., residential, commercial and industrial users) where each type of users can only access to the tariff plan designed to them. However, the differential pricing problem considered in this paper is fundamentally different from [2] where we consider customer segments in the residential sector and different groups of customers are given the same access to all the available tariff plans. In addition, each customer group will make their best choice among those offered tariffs, e.g., to minimize their energy bills. That is, if the tariffs are not designed right, most customers may not choose the tariffs targeted to them and the goal (e.g., peak demand reduction, profit maximization) of retailer will not be achieved. As a result, it is important to know customers' energy usage patterns and how customers will make their tariff choices when designing the differential pricing strategy.

With the penetration of smart meters and growing smart grid pilot projects, high resolution smart metering data become available[7]. Inspired by the above development, energy customer segmentation has attracted much attention from researchers in recent years. For instance, [8] [9] adopt machine learning based techniques (clustering) to implement customer segmentation based on customers' history load profiles. With relevant data becoming available, price sensitivity of customers

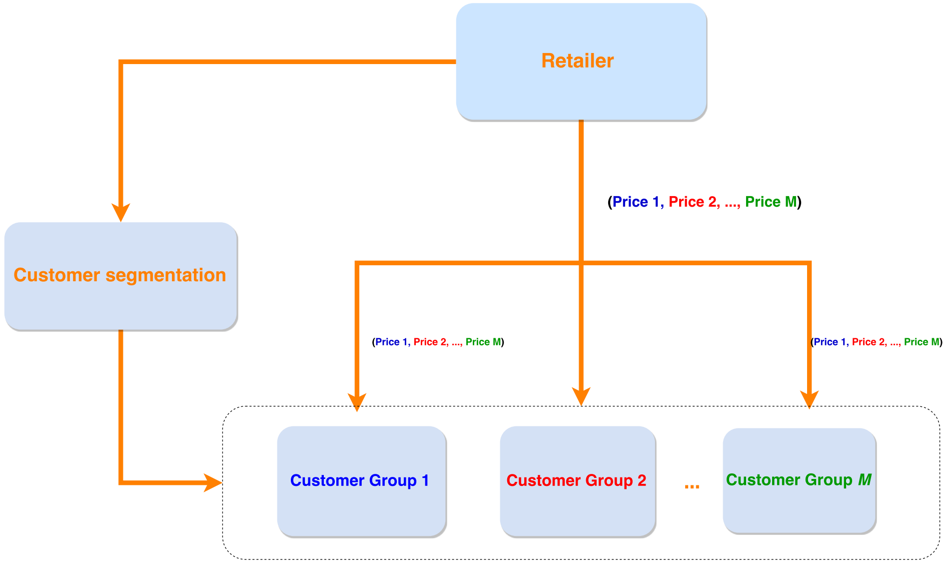

Fig. 1: Differential pricing framework

can be obtained using methods such as [5] and then be used as a attribute in customer segmentation.

Following the above analysis, in this paper, we propose a differential pricing framework for the retailer based on customer segmentation, which is illustrated in Figure 1. Firstly, the retailer implement customer segmentation and categorize customers based on their sensitivities to price signals (ToU in this paper) into different groups (e.g., price sensitive, price mid-sensitive, and price insensitive customers). Further, the optimal differential pricing problem is formulated as two-level optimization problem between the retailer and different groups of customers. At the upper level, a pricing optimization problem is formulated for the retailer to maximize its profit, and minimize the mismatch between targeted tariff plans (by the retailer) and actually selected tariff plans (by customers). At the lower-level, an optimal tariff selection problem is formulated for each customer group to minimize their bills.

Although we formulate the differential pricing problem from one retailer perspective and behaviours of other retailers are not explicitly modelled in this paper, it is worth mentioning that we are actually considering a competitive (but imperfect) retail market where the retailers are regulated by a government regulator (e.g., Ofgem in the UK). The retail market competitions from other retailers will be taken into account and reflected in the price/revenue constraints in the problem formulation of our considered retailer.

Finally, the rest of this paper is organized as follows. Customer segmentation is discussed in Section II. A benchmarked uniform ToU is presented in Section III. Further, an optimal differential pricing is proposed in Section IV. Numerical results are presented in Section V and this paper is concluded in Section VI.

II. Customer Segmentation

There are emerging research on energy customers segmentation based on real consumption profiles and price elasticity analysis [5] [8] [9] . It is well understood that machine learning techniques and data-driven framework need to be adopted to implement the customer segmentation. Due to the space limitation and main focus of this paper, we make the assumption that customer segmentation has already been completed and given as a prior in our differential pricing problem. Furthermore, we consider setting ToU prices for two critical time periods [1]: peak-demand period (5.30PM -9.30PM) and off-peak demand period (12AM - 6AM). For the simplicity of demonstration, we assume that there are three categorized groups of customers following customer segmentation: price-sensitive, price mid-sensitive and price insensitive customers. Although there could be different number of customer segments in real world implementations, the following presented optimal differential pricing approach can be generalized to any number of customer segments.

Following the above, by denoting the prices for peak demand period and off-peak demand period as p^+ and p^- respectively, the difference between prices in both time periods is therefore defined as $p^D = p^+ - p^-$. In this study, the price sensitivity of customers is defined as the amount of peak time consumption (in percentage) that customers are willing to shift from high price period to low price period. We model the price sensitivities of different customer groups (s_{se}, s_{mid}, s_{in} representing the sensitivity of price sensitive, price mid-sensitive, and price insensitive customers) as Eq (1) following a preliminary trial and error analysis of a real world smart meter data set [10], where $p^D_{se}, p^D_{mid}, p^D_{in}$ represent the price difference of peak and off-peak time periods for each customer group respectively. Note that a more dedicated price sensitivity model could be achieved via machine learning

[1]The choice is motivated by the project report of [7] that evening and midnight are two critical time periods. In the future work, we will generalize the current problem setting by considering more time periods covering 24 hours to reflect complete shifting behaviours of customers.

techniques (e.g., multiple linear regression [11], Bayesian learning [5]), which is part of our future work.

$$\begin{aligned} &s_{se} = 0.0225 \times p_{se}^D - 0.075, \\ &s_{mid} = \tfrac{0.0225}{2} \times p_{mid}^D - \tfrac{0.075}{2}, \\ &s_{in} = 0.001 \times p_{in}^D. \end{aligned} \tag{1}$$

III. A Benchmarked Uniform ToU Pricing

In this section, we formulate the uniform optimal time-of-use pricing problem as a benchmark for comparison purposes. Firstly, we denote the original energy consumption (e.g., under flat pricing) for each group of customers in peak-time period and off-peak period as $DE_{se0}^+, DE_{se0}^-, DE_{mid0}^+, DE_{mid0}^-, DE_{in0}^+, DE_{in0}^-$ respectively whereas the resulting energy consumptions in peak-time period and off-peak period under the uniform ToU are denoted as $DE_{seu}^+, DE_{seu}^-, DE_{midu}^+, DE_{midu}^-, DE_{inu}^+, DE_{inu}^-$ respectively. We make the following assumption that original energy consumptions under flat pricing have been forecast via machine learning algorithms from history data and given as a prior. The optimal time-of-use pricing problem is modelled for the retailer to maximize its profit under relevant realistic market constraints. Furthermore, the prices for peak demand period and off-peak demand period considered in this uniform ToU problem is denoted as p_u^+ and p_u^- respectively. As a result, the price sensitivity of each customer group (denoted as s_{seu}, s_{midu}, s_{inu} respectively) can be calculated following Eq (1) and thereafter the energy consumption of each customer group in peak/off-peak time period is obtained. Take the price sensitive customer group for example, the resulting energy consumptions in peak time period and off-peak period can be obtained as $DE_{seu}^+ = DE_{se0}^+ - DE_{se0}^+ \times s_{seu}$ and $DE_{seu}^- = DE_{se0}^- + DE_{se0}^+ \times s_{seu}$ respectively.

In the following, firstly we adopt a linear cost function to represent the energy procurement cost of the retailer. Furthermore, we denote the average unit cost of energy in peak time period as c^+ and that in off-peak time period as c^-. As a result, the procurement cost (denoted as CO) is given below.

$$\begin{aligned} &CO_u = c^+ \times (DE_{seu}^+ + DE_{midu}^+ + DE_{inu}^+) + \\ &c^- \times (DE_{seu}^- + DE_{midu}^- + DE_{inu}^-) \end{aligned} \tag{2}$$

Secondly, we denote the minimum and maximum price that the retailer can offer at peak time period as p_u^{min+} and p_u^{max+}. Similarly, the minimum and maximum price that the retailer can offer at off-peak time period are denoted as $p_u^{min-}$and p_u^{max-} respectively. The retailer will consider market competitions from other retailers (e.g., by predicting their retail prices) in determining its own upper and lower price bounds. As a result, we have the following constraints:

$$\begin{aligned} &p_u^{min+} \le p_u^+ \le p_u^{max+}, \\ &p_u^{min-} \le p_u^- \le p_u^{max-}. \end{aligned} \tag{3}$$

Further, there might be additional responsibilities imposed on the retailer in context of smart grids such as demand response targets. In this paper, we assume there is a preallocated target for the retailer to meet in peak demand reduction, which is defined as an small interval $[\underline{s}_{avg}, \bar{s}_{avg}]$. In other words, the peak demand reduction (in percentage) achieved by the retailer, denoted as s_{avg} must fall within the above interval. As a result, the following constraint must be met.

$$\underline{s}_{avg} \le \frac{s_{seu} \times DE_{se0}^+ + s_{midu} \times DE_{mid0}^+ + s_{inu} \times DE_{in0}^+}{DE_{se0}^+ + DE_{mid0}^+ + DE_{in0}^+} \le \bar{s}_{avg}. \tag{4}$$

Due to the retail market regulation (e.g., Ofgem in the UK), some revenue constraints must be enforced to avoid unreasonable prices are offered to customers and thus to improve the acceptability of retailer's pricing strategies. To this end, in this paper, we set a revenue cap, denoted as RE^{max}, for the retailer. As a result, we have the following constraint:

$$\begin{aligned} &RE_u = p_u^+ \times (DE_{seu}^+ + DE_{midu}^+ + DE_{inu}^+) + \\ &p_u^- \times (DE_{seu}^- + DE_{midu}^- + DE_{inu}^-) \le RE^{max} \end{aligned} \tag{5}$$

Finally, the optimal uniform time-of-use pricing problem to maximize the retailer's profit under relevant market constraints is modelled as below.

$$\begin{aligned} &\max_{p_u^-, p_u^+} RE_u - CO_u \\ &\text{subject to constraints (3), (4) and (5).} \end{aligned} \tag{6}$$

The above optimal uniform ToU pricing problem is essentially a quadratically constrained quadratic program (QCQP) (the quadratic constraint is the revenue constraint Eq (5)). In this paper, we use Matlab nonlinear programming solver *fmincon* with interior point methods (IPM) as the algorithm in our implementations.

IV. Optimal Differential Pricing

In this section, we formulated the differential pricing problem between the retailer and different groups of customers as a two-level optimization problem. At the upper-level, we design the optimal differential pricing for the retailer to maximize its profit, and minimize the mismatch between targeted tariff plans (e.g., the retailer designs a specific tariff plan targeting to a particular customer group, and expects such customers to select that tariff plan) and the actually selected tariff plans by each customer group. The retailer should consider how customers respond to the offered price plans and feed such responses back into the differential pricing design. In other words, the proposed optimal differential pricing should carry the capability of offering 'right' prices to the 'right' customers. At the lower-level, we formulate the customer-side problem as an optimal tariff selection problem. That is, given all the tariff plans available, each customer aims to choose a tariff that is most beneficial (e.g., lowest bill payment) to them. The above described two-level model captures the strong interactions between the retailer and different groups of customers in the price determination process. Recall that we assume there are three customer groups (i.e. price sensitive, price mid-sensitive and price insensitive customers) in this paper. As a result, there are in total three tariff plans offered by the retailer that are available to each customer group.

Denote the tariff plan targeted to each customer group $n \in \{1, 2, 3\}$ as a price vector $\mathrm{p_m} = (p_m^+, p_m^-)$ $m = 1, 2, 3$ where n represent the index of price sensitive, price mid-sensitive and price insensitive customer group respectively whereas m represent the index of tariff plan targeted to price sensitive, price mid-sensitive and price insensitive customer group. In addition, p_m^+ and p_m^- represent peak time price and off-peak price of tariff plan m. Finally, the problem formulations for the retailer and its customers are given below.

A. Optimal Tariff Selection for Customers

Given the tariff plans offered by the retailer, i.e. $\mathrm{p_m},\ m = 1,2,3$, the aim of each customer group $n \in \{1,2,3\}$ is to select a tariff from the above tariff plans to minimize his/her payment bill. Note that from the perspective of customers, they do not know which tariff plans are targeted to them. Therefore, this constitute a optimal tariff selection problem for them.

The price sensitivity of each customer group n under each of the above tariff plans can be derived based on Eq (1) and denoted as $s_{nm},\ n = 1,2,3;\ m = 1,2,3$ where s_{nm} represents the price sensitivity of customer group n under tariff plan $\mathrm{p_m}$. Same as in Section III, by denoting the original energy consumptions (e.g., under flat pricing) of each customer group in peak-time period and off-peak period as DE_n^{+0} and DE_n^{-0}, the energy consumption of each customer group under each of the above three offered tariff plans in both peak-time and off-peak periods can be derived in the same way as in Section III and are denoted as $DE_{nm}^+,\ n = 1,2,3;\ m = 1,2,3$ and $DE_{nm}^-,\ n = 1,2,3;\ m = 1,2,3$ respectively[2].

As a result, the optimal tariff selection problem of each customer group $n \in \{1,2,3\}$ is formulated below.

$$\begin{aligned} \mathrm{sp_n^*} = \underset{\mathrm{sp_n}\in\{\mathrm{p_m},\forall m=1,2,3\}}{\arg\min} \quad & (sp_n^+ \times DE_{nm}^+ \\ & + sp_n^- \times DE_{nm}^-),\ n = 1,2,3. \end{aligned} \tag{7}$$

In the above, $\mathrm{sp_n} = (sp_n^+, sp_n^-)$ are the vector of decision variables which represent the tariff plans available to customer group n. Finally, the optimal tariff plan can be found for each customer group n and is denoted as $\mathrm{sp_n^*} = (sp_n^{+*}, sp_n^{-*})$. The corresponding price sensitivity as well as energy consumption of customer group n in peak and off-peak period under optimal selected tariff plan can then be obtained and denoted as s_n^*, DE_n^{+*} and DE_n^{-*} respectively.

B. Optimal Tariff Design for the Retailer

In this subsection, an optimal differential pricing problem is formulated for the retailer to maximize its profit and also minimize the mismatch between the targeted tariff plans (offered by the retailer to each customer group) and the actually chosen tariff plans by each customer group.

A linear cost function is adopted to represent the energy procurement cost of the retailer. Furthermore, we denote the average unit cost of energy in peak time period as c^+ and that in off-peak time period as c^-. Therefore, the procurement cost (denoted as CO_d) is given below.

$$CO_d = \textstyle\sum_{n=1}^{3}(c^+ \times DE_n^{+*} + c^- \times DE_n^{-*}) \tag{8}$$

[2]In real implementations, interactive service platforms such as price comparison service website (e.g., https://www.uswitch.com/ in the UK) are required to be in place to derive price sensibilities and select optimal tariffs on behalf of customers.

Secondly, we denote the minimum price and maximum price that the retailer can offer to each customer group in peak and off-peak time period as p_m^{min+}, p_m^{max+} and p_m^{min-}, $p_m^{max-}, m = 1,2,3$ respectively. As a result, we have the following constraints:

$$\begin{aligned} & p_m^{min+} \le p_m^+ \le p_m^{max+}, \\ & p_m^{min-} \le p_m^- \le p_m^{max-}.\ \forall m = 1,2,3 \end{aligned} \tag{9}$$

Same as in Section III, it is assumed that there is a predefined target in terms of the percentage of peak demand reduction imposed on retailer. As a result, the following inequality must be satisfied.

$$\underline{s}_{avg} \le \frac{\sum_{n=1}^{3} s_n^* \times DE_n^{+*}}{\sum_{n=1}^{3} DE_n^{+0}} \le \bar{s}_{avg}. \tag{10}$$

Further, due to the retail market regulation, we add a revenue constraint to ensure that reasonable prices are offered and thus to improve the acceptability of retailer's pricing strategies. That is, there exists a total revenue cap, denoted as RE^{max} for the retailer. Thus, we have the following constraint:

$$RE_d = \textstyle\sum_{n=1}^{3}(sp_n^{+*} \times DE_n^{+*} + sp_n^{-*} \times DE_n^{-*}) \le RE^{max} \tag{11}$$

To minimize the mismatch between the targeted tariff plans and the actually chosen tariff plans by each customer group, a penalty term is added to the objective function to penalize the mismatch and therefore guide the optimal prices search direction. We design the penalty function as Eq (12) where K_m is a penalty constant dependent on each customer group.

$$J_m(\mathrm{p_m}) = \begin{cases} 0 & \text{if } \mathrm{p_m} = \mathrm{sp_n^*} \\ K_m & \text{otherwise} \end{cases} \tag{12}$$

Finally, the optimal differential pricing problem for the retailer is formulated as below.

$$\begin{aligned} & \max_{\mathrm{p_m},\forall m=1,2,3} RE_d - CO_d - J_m \\ & \text{subject to constraints (9), (10), (11).} \end{aligned} \tag{13}$$

C. Solution Algorithms

Due to the proposed bilevel model has integer decision variables in the lower-level problem Eq (7) and the conditional expressions Eq (12) in the upper level problem, it is extremely difficult to use conventional nonlinear programming methods to solve the problem. Metaheuristic algorithms such as genetic algorithms are computationally simple and powerful and are very good tools for non-convex optimization problems since they have more chances to find the global optimal solutions. Furthermore, metaheuristic algorithms are often the only method available for some ill-defined optimization problem such as those involving with non-differentiable, discontinuous, or non-analytically definable functions, and the optimization problem of our proposed bilevel model is one of such cases.

In our proposed genetic algorithms, binary encoding and deterministic tournament selection without replacement is adopted [12]. For the crossover and mutation operations, we employ uniform crossover and bit flip mutation respectively

Algorithm 1 GA based pricing optimization algorithm to (13) executed by the retailer

1: Population Initialization, i.e. generating a population of PN chromosomes randomly; each chromosome represents a strategy (i.e., a group of tariff plans) of the retailer.
2: **for** i=1 to PN **do**
3: The retailer announces strategy i to customers.
4: Each customer group solves the optimization problem Eq (7). Therefore, the retailer obtains the responsive demand and optimally selected tariff plan from each customer group.
5: Fitness evaluation and constraint handling [15] to satisfy constraints (9 - 11).
6: **end for**
7: A new generation of chromosomes are created by using deterministic tournament selection without replacement, uniform crossover and bit flip mutation [12] [13] [14].
8: Steps 2-7 are repeated until the stopping condition is reached.
9: The retailer announces final tariff plans to all customer groups.

[13] [14]. The constraints are handled by the approach proposed in [15]. Readers are referred to [16] for more details on our adopted GAs.

Finally, the GAs based optimization algorithm is given in Algorithm 1. At the end, the most profitable and best accepted differential tariff plans are found for the retailer.

V. Simulation Results

A. Simulation Set-up

In this section, we conduct simulations to evaluate the proposed optimal differential ToU and the benchmark pricing (uniform ToU) on a day-to-day basis [3]. We consider a pool of 300 customers where three types of customers are assumed to have been identified based on customer segmentation and are evenly distributed (i.e. 100 price sensitive customers, 100 price mid-sensitive customers and 100 price insensitive customers). Firstly, we select c^- and c^+ in Eqs. (2) and (8) as 3 and 15 cents for both uniform pricing and differential pricing problems. In addition, p_u^{min+} and p_u^{max+} in the uniform pricing problem are set to 25 and 35 cents respectively while p_u^{min-} and p_u^{max-} are set to 5 and 15 cents. For differential pricing, we set p_m^{min+}, p_m^{max+}, p_m^{min-}, p_m^{max-}, $\forall m \in \{1,2,3\}$ as follows:

$$\begin{aligned}
&p_1^{min+} = 32,\ p_1^{max+} = 35,\\
&p_1^{min-} = 5,\ p_1^{max-} = 8;\\
&p_2^{min+} = 28,\ p_2^{max+} = 31,\\
&p_2^{min-} = 9,\ p_2^{max-} = 12;\\
&p_3^{min+} = 25,\ p_3^{max+} = 27,\\
&p_3^{min-} = 13,\ p_3^{max-} = 15.
\end{aligned}$$

[3]Although the current ToU practice (e.g., Economy 7 in the UK) fixes the prices for a longer period (e.g., a season), in this paper we consider the ToU pricing on a daily basis in the smart grid environment.

TABLE I: Disaggregated results under Uniform ToU Pricing

Customer Group	Revenue	Cost	Profit	Peak shifting
Price sensitive	188.69	83.32	105.37	0.4446
Price mid-sensitive	229.75	104.66	125.09	0.2223
Price insensitive	266.56	123.78	142.78	0.0231
Overall	**685.00**	**311.76**	**373.24**	**0.230**

We set $\underline{s}_{avg}$ and $\bar{s}_{avg}$ in Eqs. (4) and (10) to 0.15 and 0.23 respectively, i.e. a minimum of 15% of peak demand are required to be reduced/shifted by using uniform/differential ToU pricing but the peak demand reduction/shifting should not be greater than 23% to avoid peak demand rebound effects. Furthermore, the maximum revenue RE^{max} in Eqs. (5) and (11) is set to \$685. The original energy consumptions of each customer group under flat pricing in peak time and off-peak time periods are set to 800 kwh and 200 kwh respectively. The price sensitivities of each customer group are calculated based on Eq (1) and the resulting energy consumption of each customer group under peak time period and off-peak time period can be obtained in the same way as described in Section III.

B. Results of Uniform ToU

With the simulations set up, we solve the optimal uniform ToU pricing problem Eq (6) using solver *fmincon* in Matlab R2015a.

The optimal prices for uniform ToU are obtained as $p_u^+ = 31.70$ cents and $p_u^- = 8.61$ cents. The revenue, cost and profit under the above optimal uniform ToU prices are \$685.00, \$ 311.76, and \$373.24 respectively. The peak energy consumption reduction constraint Eq (4) is active, i.e., $s_{avg} = 0.23$.

Furthermore, the disaggregated revenue, profit, cost, and peak energy consumption reduction under each customer group are given in Table I. From the above results, we can easily reach some interesting findings. For instance, under the obtained uniform ToU, price insensitive customers only reduce a small fraction (i.e. 2.31%) of their peak usages whose contribution to the overall peak reduction (i.e. 0.77%) is negligible compared with other customer groups. However, due to the high peak time price, price-insensitive customers would need to pay much more bills than price sensitive/mid-sensitive customers. This could possibly lead to a low acceptability of ToU pricing among customers. On the other hand, price sensitive customers might be willing to reduce more peak usages if more incentives (e.g., under a tariff plan with higher peak price/lower off-peak price than the above uniform ToU prices) are offered. In that case, price sensitive customers would shift more peak usage, which not only leads to further reduced bills for themselves but also a reduced energy procurement cost for the retailer. Based on the above analysis, we designed an optimal differential pricing to accommodate the above findings drawn from uniform ToU where simulation results are given in the following subsection.

C. Results of Differential ToU

We solve the optimal differential pricing problem Eq (13) using GAs based optimization method (see Algorithm 1). The

TABLE II: Parameter settings of GAs

Parameter Name	Symbol	Values
Chromosome Length	L_g	7
Population Size	PN	500
Mutation Probability	P_g	0.005
Terminate Generation	T_g	500

TABLE III: Results under differential Pricing

Customer Group	**Revenue**	**Cost**	**Profit**	**Peak shifting**
Price sensitive	181.66	76.35	105.31	0.5172
Price mid-sensitive	235.98	111.02	124.96	0.1560
Price insensitive	244.71	124.85	119.86	0.0120
Overall	**662.35**	**312.22**	**350.13**	**0.2284**

parameters of the proposed genetic algorithm are set as Table II. The obtained differential pricing targeted to each customer group are given below.

$$p_1^+ = 34.37,\ p_1^- = 7.97 \ \text{ for price sensitive customers}$$
$$p_2^+ = 29.12,\ p_2^- = 11.94 \ \text{ for mid-sensitive customers}$$
$$p_3^+ = 26.86,\ p_3^- = 14.97 \ \text{ for insensitive customers}$$

Furthermore, the revenue, profit, cost, and peak energy consumption reduction under the above obtained differential pricing for each customer group are given in Table III. Compared with optimal uniform ToU prices, the tariff plan targeted to price sensitive customers (and actually selected by them) has higher peak time price (i.e., 34.37 cents) but lower off-peak time price (i.e., 7.97 cents). As shown in Table III, price sensitive customers have more incentives under differential pricing, which results in a lower bill (i.e. $181.66) for themselves and lower energy procurement cost (i.e. $76.35) for the retailer. On the other hand, the tariff plan targeted to price insensitive customers (and actually selected by them) is 26.86 cents for peak time price and 14.97 cents for off-peak time price, which results in a lower bill (i.e. $244.1) for price insensitive customers compared with uniform ToU pricing. From the above analysis [4], it reveals a great potential of differential pricing that it could offer 'personalized' tariff plans to each customer group and therefore create a better price image for the retailer, which will help lead to an improved acceptability of dynamic pricing among customers and an increased customer satisfaction.

VI. Conclusion and Future Work

In this paper, we propose a differential pricing framework for the smart grid retail market and formulate the interactions between the retailer and each customer group in the optimal differential pricing as a bilevel optimization problem. Firstly, a pricing optimization problem is formulated for the retailer to maximize its profit and minimize the mismatch between targeted tariff plans (by the retailer) and actually selected tariff plans (by customers). Secondly, an optimal tariff selection problem is formulated for each customer group to minimize their bills. Finally, a genetic algorithms based solution method is developed to solve the bilevel model with simulation results confirmed the effectiveness of our proposed differential pricing strategy. In our future work, firstly we will develop a data-driven customer segmentation framework based on customers' load profiles and their price sensitivities. Secondly, we will integrate such a data-driven framework into the optimal differential pricing framework proposed in this paper. Finally, we will generalize the current differential pricing framework to accommodate real time pricing.

[4] We implement a further simulation by setting RE^{max} and $\bar{s}_{avg}$ in the Uniform ToU problem to 662.35$ and 0.2284 respectively (optimal values obtained in differential pricing as detailed in Table III). The same conclusion can be reached from these simulation results but details are omitted here due to space limitations

Acknowledgment

This work was partly supported the Engineering and Physical Sciences Research Council, UK (Grant No. EP/K002252/1). The first author would like to thank Durham Energy Institute for the DEI Small Grant funding.

References

[1] Ofgem, "Transition to smart meters," https://www.ofgem.gov.uk/electricity/retail-market/metering/transition-smart-meters, accessed 16 January 2017.

[2] P. Yang, G. Tang, and A. Nehorai, "A game-theoretic approach for optimal time-of-use electricity pricing," *IEEE Transactions on Power Systems*, vol. 28, no. 2, pp. 884–892, 2013.

[3] B. Chai, J. Chen, Z. Yang, and Y. Zhang, "Demand response management with multiple utility companies: A two-level game approach," *IEEE Transactions on Smart Grid*, vol. 5, no. 2, pp. 722–731, 2014.

[4] F.-L. Meng and X.-J. Zeng, "A bilevel optimization approach to demand response management for the smart grid," in *Evolutionary Computation (CEC), 2016 IEEE Congress on*. IEEE, 2016, pp. 287–294.

[5] ——, "A profit maximization approach to demand response management with customers behavior learning in smart grid," *IEEE Transactions on Smart Grid*, vol. 7, no. 3, pp. 1516–1529, 2016.

[6] X. Fu, X.-J. Zeng, X. R. Luo, D. Wang, D. Xu, and Q.-L. Fan, "Designing an intelligent decision support system for effective negotiation pricing: A systematic and learning approach," *Decision Support Systems*, 2017.

[7] I. S. S. D. Archive, "Cer smart metering project," http://www.ucd.ie/issda/, accessed 15 January 2017.

[8] S. Haben, C. Singleton, and P. Grindrod, "Analysis and clustering of residential customers energy behavioral demand using smart meter data," *IEEE Transactions on Smart Grid*, vol. 7, no. 1, pp. 136–144, 2016.

[9] C. Flath, D. Nicolay, T. Conte, C. van Dinther, and L. Filipova-Neumann, "Cluster analysis of smart metering data," *Business & Information Systems Engineering*, vol. 4, no. 1, pp. 31–39, 2012.

[10] C.-L. N. Revolution, "Project data," http://www.networkrevolution.co.uk/resources/project-data/, accessed 15 January 2017.

[11] Q. Ma and X.-J. Zeng, "Demand modelling in electricity market with day-ahead dynamic pricing," in *2015 IEEE International Conference on Smart Grid Communications (SmartGridComm)*. IEEE, 2015, pp. 97–102.

[12] T. Blickle and L. Thiele, "A comparison of selection schemes used in evolutionary algorithms," *Evolutionary Computation*, vol. 4, no. 4, pp. 361–394, 1996.

[13] G. Syswerda, "Uniform crossover in genetic algorithms," in *Proceedings of the 3rd International Conference on Genetic Algorithms*, 1989, pp. 2–9.

[14] P. Reed, B. Minsker, and D. Goldberg, "Designing a competent simple genetic algorithm for search and optimization," *Water Resources Research*, vol. 36, no. 12, pp. 3757–3761, 2000.

[15] K. Deb, "An efficient constraint handling method for genetic algorithms," *Computer methods in applied mechanics and engineering*, vol. 186, no. 2, pp. 311–338, 2000.

[16] F.-L. Meng and X.-J. Zeng, "A stackelberg game-theoretic approach to optimal real-time pricing for the smart grid," *Soft Computing*, vol. 17, no. 12, pp. 2365–2380, 2013.