Equitable Time-Varying Pricing Tariff Design

-------2023 NAPS

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Oct. 17. 2023

What will the future electricity prices look like?

- *Background*
- *Methodology & Solution*
- *Results*

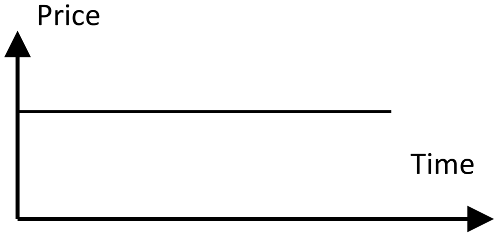
Background

Why this topic?

Background

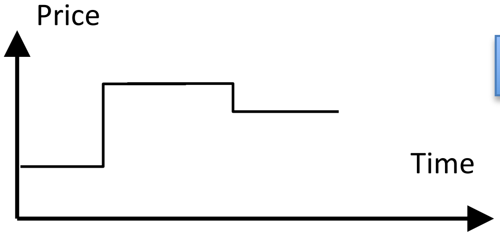
Constant tariffs

- Flat prices over long time



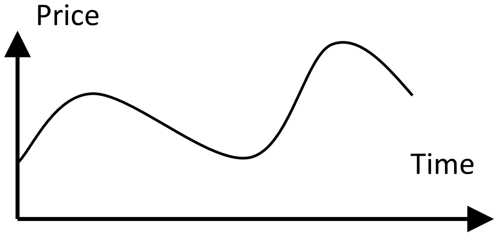
Time of Use (ToU) tariffs

- Predefined non-flat prices over long time
- Generally high, low, normal



Time-varying tariffs

- Hourly different price
- Incentive consumers’ flexible response



Challenges

- Reflect wholesale market prices, distribution grid security constraints, and consumers’ willingness to respond
- Current research mentions price design should reflect equity, as DER integration will benefit or burden different consumers

[1] S. Burger, I. Schneider, A. Botterud, and I. Pérez-Arriaga, “Fair, equitable, and efficient tariffs in the presence of distributed energy resources,” Consumer, Prosumer, Prosumager: How Service Innovations will Disrupt the Utility Business Model, p. 155, 2019
[2] Cahana, M., Fabra, N., Reguant, M., & Wang, J. (2022). The distributional impacts of real-time pricing.

Equality issues

- Allocatively equity: treat identical customers equally
- Distributionally equity: guarantee vulnerable customer groups pay an acceptable amount for electricity service
- Transitional equity: equity when transition from one tariff to another

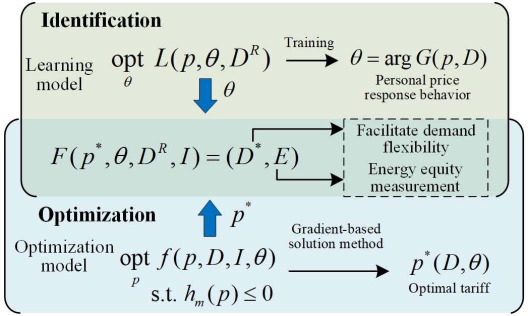
Contributions:

- Design effective and equitable tariff
- Capture price-response behavior and embedded social demographics information of consumers

Methodology & Solution

How to formulate the tariff design problem?

Equitable and effective tariff design model



- Non-linear, high-dimensional, and determined by the consumer's subjective preference.
- Two methods to identify the price response behavior:

Piece-wise linear model – ToU tariff

Neural network – Time-varying tariff

Optimization

Energy burden = Electricity bill / Income

Low-income consumer energy burden

$$\min_{\boldsymbol{p}_i} f = \sum_{i \in \mathcal{I}} \left(\left[\frac{\boldsymbol{D}_i^T \boldsymbol{p}_i}{I_i} - \overline{E} \right]^+ \right)^2 + \alpha \|\boldsymbol{p}_i - \boldsymbol{\lambda}\|_2^2$$

price difference

s.t.

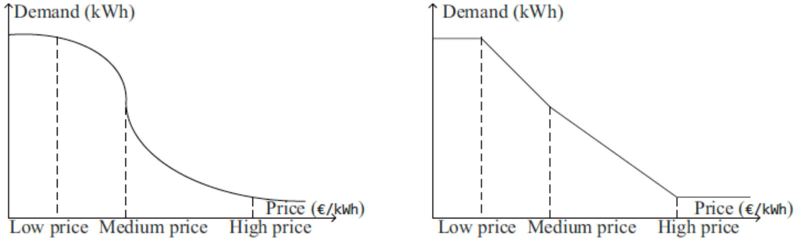
$\boldsymbol{D}_i = G_i(\boldsymbol{p}_i | \boldsymbol{\theta}_i)$ Price response behavior

$\sum_{i \in \mathcal{I}} \boldsymbol{D}_i^T \boldsymbol{p}_i \geq C + \boldsymbol{D}_{0,i}^T \boldsymbol{\lambda}$ Revenue recovery

$\sum_{i \in \mathcal{I}} D_{i,t} \leq (1-\beta) \sum_{i \in \mathcal{I}} D_{0,i,t}, \ \forall t \in \{\text{PeakHours}\}$ Demand reduction target

Methodology

Identification – ToU tariff

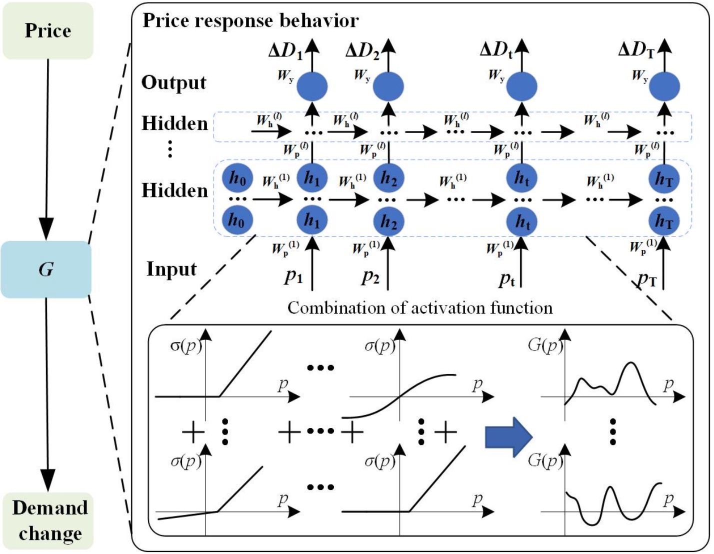


(a) Actual price response (b) Linearized prices response

- model price response behavior as a piece-wise linear model
- Only low, medium, and high prices

$$D_{i,t}(\pi_{i,t}) = \begin{cases} D_{i,t,\max}, & \text{if } 0 \leq \pi_{i,t} \leq \pi_{\text{low}}; \\ a_{i,t,1} * \pi_{i,t} + b_{i,t,1}, & \text{if } \pi_{\text{low}} \leq \pi_{i,t} \leq \pi_{\text{med}}; \\ a_{i,t,2} * \pi_{i,t} + b_{i,t,2}, & \text{if } \pi_{\text{med}} \leq \pi_{i,t} \leq \pi_{\text{high}}; \\ D_{i,t,\text{low}}, & \text{if } \pi_{\text{high}} \leq \pi_{i,t} \end{cases}$$

Identification – Time-varying tariff



$$\min_{\boldsymbol{\theta}} L = \|G_i(\boldsymbol{p}_i|\boldsymbol{\theta}) - \boldsymbol{D}_i^R\|_2^2$$

- Past price data
- Observed consumer demand in response to the instructed prices

Solution algorithm

- **ToU Tariff** – The piecewise linear modeling method formulates a mix-integer non-linear optimization model, which can be solved by GUROBI 9.5.2 directly
- **Time-varying tariff** – The neural network modeling method formulates a non-linear optimization problem with a quadratic objective and neural network structure constraints. We propose a gradient-based solution algorithm with barrier functions to deal with constraints.

The gradient-based method with barrier function

$$\begin{aligned}\min_{\boldsymbol{p}_i(\mu)} \ F_0 &= \mu f + \sum_{m\in M} \varphi_m(C) \\ &= \mu\Big(\sum_{i\in\mathcal{I}} \Big(\Big[E_i - \overline{E}\Big]^+\Big)^2 + \alpha\|\boldsymbol{p}_i - \boldsymbol{\lambda}\|_2^2\Big) \\ &+ \sum_{t\in\{\mathrm{PK}\}} \ln(C_t) + \ln(C_1)\end{aligned} \tag{11}$$

$$C_t = -\sum_{i\in\mathcal{I}} D_{i,t} + (1-\beta) * \sum_{i\in\mathcal{I}} D_{0,i,t}, \ \ \forall t \in \{\mathrm{PeakHours}\} \tag{12}$$

$$C_1 = -\sum_{i\in\mathcal{I}} \boldsymbol{D}_i^T \boldsymbol{p}_i + \boldsymbol{D}_{0,i}^T \boldsymbol{\lambda} \tag{13}$$

$$\begin{aligned}\frac{\partial F_0}{\partial p_{i,t}} &= \frac{\partial F_0}{\partial E_i}\left(\frac{\partial E_i}{\partial D_{i,t}}\frac{\partial D_{i,t}}{\partial p_{i,t}} + \frac{\partial E_i}{\partial p_{i,t}}\right) + \sum_m \frac{\partial \varphi_m}{\partial p_{i,t}} \\ &= \frac{2\mu(E_i - E_{\mathrm{bond}})}{I_i}\left(D_{i,t} + \frac{\partial D_{i,t}p_{i,t}}{\partial p_{i,t}}\right) \\ &- \delta(t)\frac{\partial D_{i,t}}{\partial p_{i,t}}\frac{1}{C_t} - \left(D_{i,t} + \frac{\partial D_{i,t}p_{i,t}}{\partial p_{i,t}}\right)\frac{1}{C_1}\end{aligned}$$

$$\delta(t) = \begin{cases} 1, & \text{if } t \in \{\mathrm{PeakHours}\} \\ 0, & \mathrm{OTW}\end{cases}$$

$$\begin{aligned}\frac{\partial D_t}{\partial p_{i,t}} &= \frac{\partial D_t}{\partial \boldsymbol{h}_t^{(L)}} \prod_{l=2}^{L}\left(\frac{\partial \boldsymbol{h}_t^{(l)}}{\partial \boldsymbol{h}_t^{(l-1)}} + \frac{\partial \boldsymbol{h}_t^{(l)}}{\partial \boldsymbol{h}_{t-1}^{(l)}}\right)\left(\frac{\partial \boldsymbol{h}_t^{(1)}}{\partial p_{i,t}} + \frac{\partial \boldsymbol{h}_t^{(1)}}{\partial \boldsymbol{h}_{t-1}^{(1)}}\right) \\ &= \boldsymbol{W}_y \frac{\partial \sigma}{\partial \boldsymbol{h}_t^{(L)}} \prod_{l=2}^{L}\left(\frac{\partial \sigma}{\partial \boldsymbol{h}_t^{(l-1)}}\boldsymbol{W}_p^{(l)} + \frac{\partial \sigma}{\partial \boldsymbol{h}_{t-1}^{(l)}}\boldsymbol{W}_h^{(l)}\right) \\ &* \left(\frac{\partial \sigma}{\partial p_{i,t}}\boldsymbol{W}_p^{(1)} + \frac{\partial \sigma}{\partial \boldsymbol{h}_{t-1}^{(1)}}\boldsymbol{W}_h^{(1)}\right)\end{aligned}$$

Convergence is dominated by neural network structure. Learned from the following literature, we prove the convergency of the whole algorithm

[1] Z. Allen-Zhu, Y. Li, and Z. Song, "On the convergence rate of training recurrent neural networks," Advances in neural information processing systems, vol. 32, 2019

[2] S. Du, J. Lee, H. Li, L. Wang, and X. Zhai, "Gradient descent finds global minima of deep neural networks," in International conference on machine learning. PMLR, 2019, pp. 1675–1685

Results

What is the performance of our method

Data and Results

Dataset

- ToU tariff and corresponding demand data come from the **Low Carbon London project**
- Time-varying tariff and corresponding base demand data comes from **ERCOT**, and the response demand data calculated by an **agent model**

$$\min_{\boldsymbol{D}_{\mathrm{r}},\boldsymbol{D}_{\mathrm{s}}} \ \boldsymbol{p}^T\boldsymbol{D} + c_1\boldsymbol{D}_{\mathrm{r}}^2 + c_2\boldsymbol{D}_{\mathrm{s}}^2$$

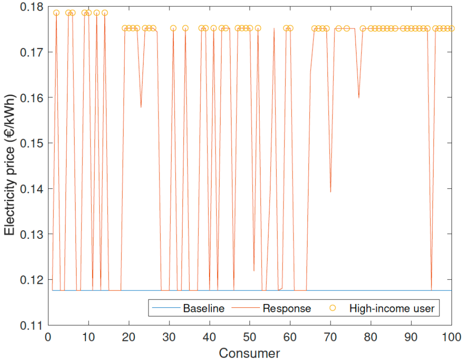
$$\boldsymbol{D} = \boldsymbol{D}_0 + \boldsymbol{D}_{\mathrm{r}} + \boldsymbol{D}_{\mathrm{s}}$$

$$\text{s.t.} \ \sum_{t\in T} D_{\mathrm{s},t} = 0$$

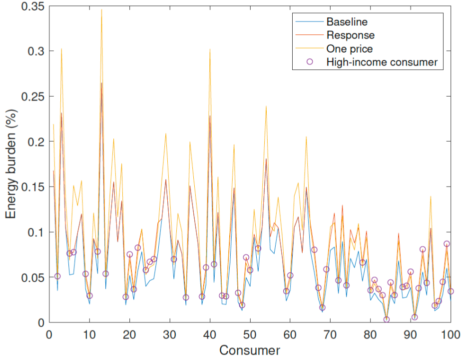
$$\underline{D_{\mathrm{s}}} \leq \boldsymbol{D}_{\mathrm{s}} \leq \overline{D_{\mathrm{s}}}$$

$$\underline{D_{\mathrm{r}}} \leq \boldsymbol{D}_{\mathrm{r}} \leq \overline{D_{\mathrm{r}}}$$

ToU tariff results



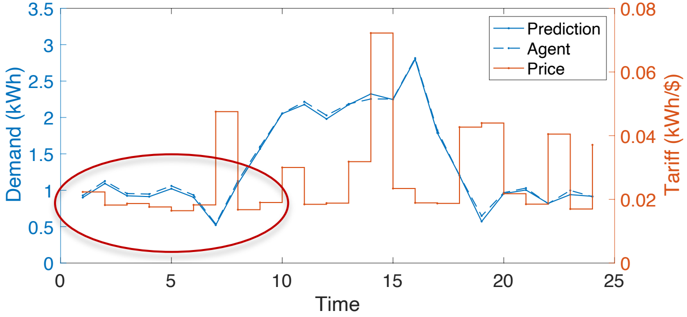
High-income consumers take high tariff, low-income consumers take low tariff, almost keep the original tariff, avoiding negative effect in DR



Energy burden proportionally changes, i.e., high-income consumers' increase a little, while low-income consumers' benefit a lot

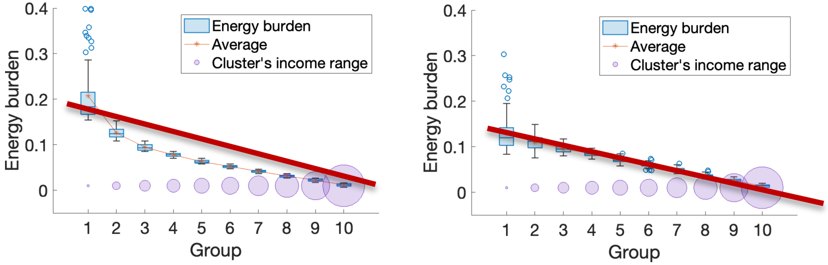
Time-varying tariff results

Behavior identification



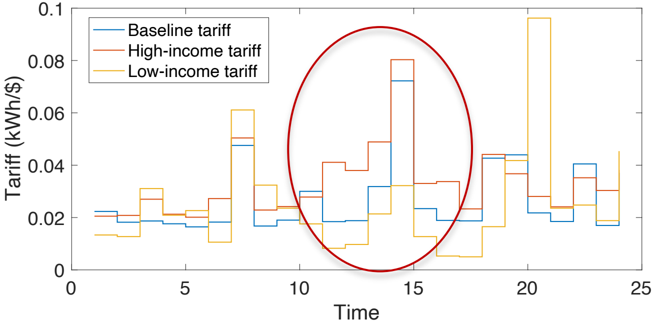
Accuracy capture price response behavior

Energy burden under baseline & modified tariff



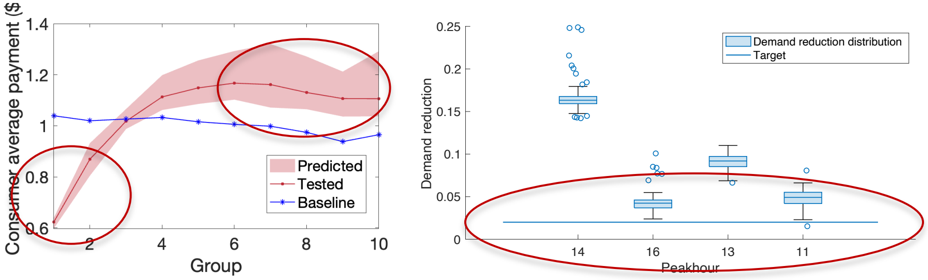
- Redistributed the energy burden among consumers
- Provide protection to low-income consumers during DR

Equitable and efficient tariff



Slightly change for different group consumer

Validation



- Variation in consumers' payment decrease with energy burden
- Robustness peak demand reduction performance

Reference

- S. Burger, I. Schneider, A. Botterud, and I. Pérez-Arriaga, "Fair, equitable, and efficient tariffs in the presence of distributed energy resources," Consumer, Prosumer, Prosumager: How Service Innovations will Disrupt the Utility Business Model, p. 155, 2019.
- The Mercury News, "Pge monthly bills could jump for many customers due to new state law," https://www.mercurynews.com/2023/04/12/pge-month-bill-jump-electric-gas-price-consumer-utility-income-economy/?clearUserState=true.
- J. Drgoňa, A. R. Tuor, V. Chandan, and D. L. Vrabie, "Physics-constrained deep learning of multi-zone building thermal dynamics," Energy and Buildings, vol. 243, p. 110992, 2021.
- A. Drehobl, R. L., and A. R., "How high are household energy burdens," Washington, DC: American Council for an Energy-Efficient Economy, Tech. Rep., 2020.
- S. Du, J. Lee, H. Li, L. Wang, and X. Zhai, "Gradient descent finds global minima of deep neural networks," in International conference on machine learning. PMLR, 2019, pp. 1675–1685.
- Z. Allen-Zhu, Y. Li, and Z. Song, "On the convergence rate of training recurrent neural networks," Advances in neural information processing systems, vol. 32, 2019

Go back to the first question

What will the future electricity prices look like :

- ToU or Time-varying tariffs, but need to reflect consumers' willingness to respond;
- Consumer-centric; effectively capture consumers' behavior;
- Address energy equity issues, especially for low-income consumers.

California started using high electricity prices (fixed parts) for high-income consumers

Thanks!