Equitable Time-Varying Pricing Tariff Design: A Joint Learning and Optimization Approach

--------6th AES workshop

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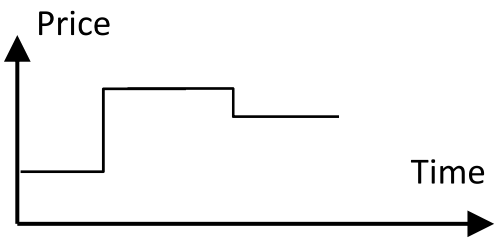
What will the future electricity prices look like?

- *Background*
- *Methodology*
- *Results*

Background

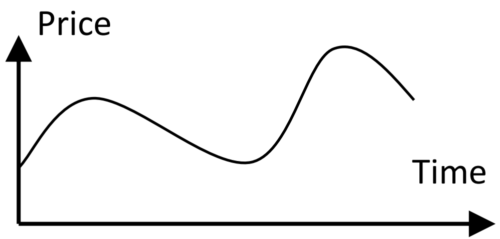
Time of Use (ToU) tariffs

- Predefined non-flat prices over long time
- Generally high, low, normal
- **Problem: Ineffective & Create another peak**



Time-varying tariffs

- Hourly different price
- Incentive consumers' flexible response
- **Problem: Incentive effectiveness & Affordability**



Challenges & Contribution

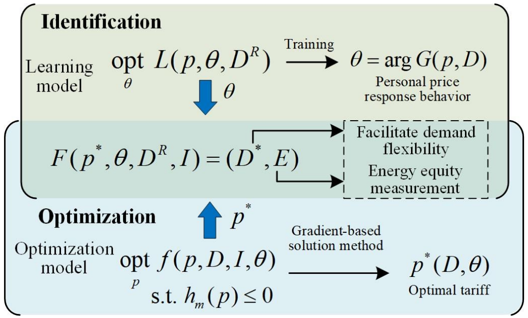
- Reflect wholesale market prices, distribution grid security constraints, and consumers' willingness to respond
- Price volatility increases the electricity cost for low-income consumers

Design effective and equitable tariff:

- A joint learning and optimization approach
- Capture time-coupled price-response behavior and social demographics of consumers

Methodology

Equitable and effective tariff design model



Optimization

We cluster consumers according to energy burden

Energy burden minimization

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

Price difference minimization

s.t.

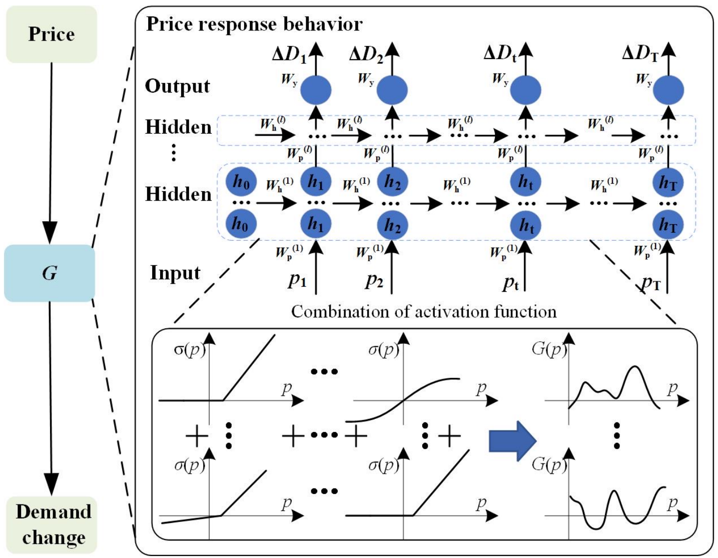
$\boldsymbol{D}_i = G_i(\boldsymbol{p}_i|\boldsymbol{\theta}_i)$ Price response behavior

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

$\boldsymbol{p}_i = \boldsymbol{p}_j,\ \forall i,j \in \mathcal{I}_n, \forall n \in \mathcal{N}$ Clustering

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

Identification



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

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

Methodology

Agent model generates synthetic response data

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

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

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

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

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

Considering shiftable and interruptible demand, adjust preference parameters c_1 and c_2 for different consumers.

Solution algorithm

The gradient-based method with barrier function

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

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

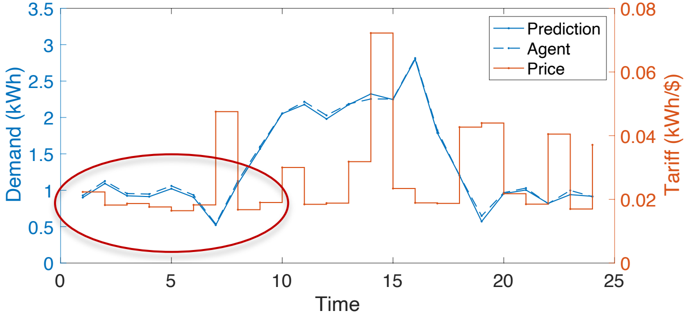
$$C_1 = -\sum_{i\in\mathcal{I}} \boldsymbol{D}_i^T\boldsymbol{p}_i + \boldsymbol{D}_{0,i}^T\boldsymbol{\lambda} \tag{13}$$

Convergence is dominated by RNN structure, proof can be found in the literature.

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
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

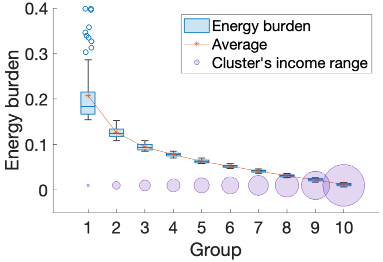
Results

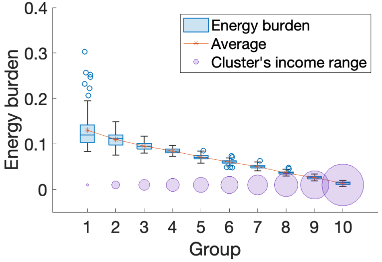
Behavior identification



Accuracy capture price response behavior

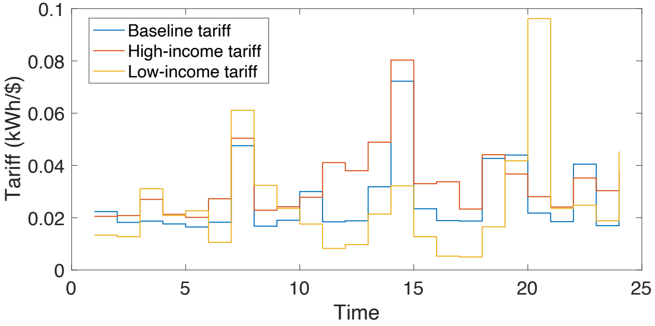
Energy burden under baseline & modified tariff





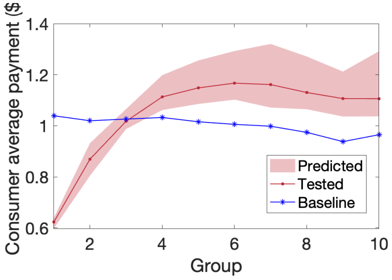
- Redistributed the energy burden among consumers
- Provide protection to low-income consumers during DR

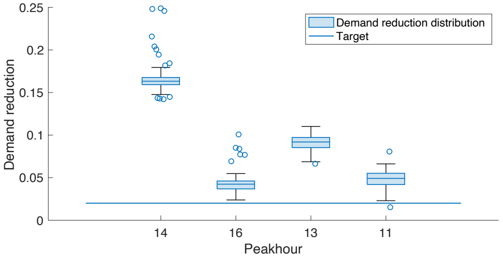
Equitable and efficient tariff



Slightly change for different group consumer

Validation





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

Reference

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Go back to the first question

What will the future electricity prices look like :

- Time-varying tariffs, but need to balance affordability and effectiveness;
- 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. We are now entering a new era.

Thanks!