Saturation Effects in Equitable Demand Response Tariff Design

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Abstract

While residential consumers' electricity demands are becoming increasingly responsive to prices due to growing awareness and adoption of smart home management devices, they cannot respond to price changes indefinitely. Modeling this saturation effect in consumer price responses is crucial to ensure that demand response will not add excessive energy cost burdens. **This work proposes an optimization model to design price response events while ensuring energy equity considering the income status and the response saturation effect of each consumer**. The proposed method uses energy burden to measure energy equity and builds machine learning model and piecewise linear model to express the response behaviors of each consumer. **We formulate the tariff design problem as a non-linear optimization model to achieve a demand reduction target while minimizing the energy burden and sharing the economic expense proportionally**. We use real-world datasets in the case study to obtain the personalized tariffs, energy consumption, and energy burden for each consumer and find the effectiveness of personalized tariffs in reducing energy burdens. By concluding the results, we derive that our method reduces consumers' energy burden difference and protects low-income consumers from the adverse effects of price variations.

Proposed method

We formulate the energy equitable tariff design problem using non-linear programming as follows:

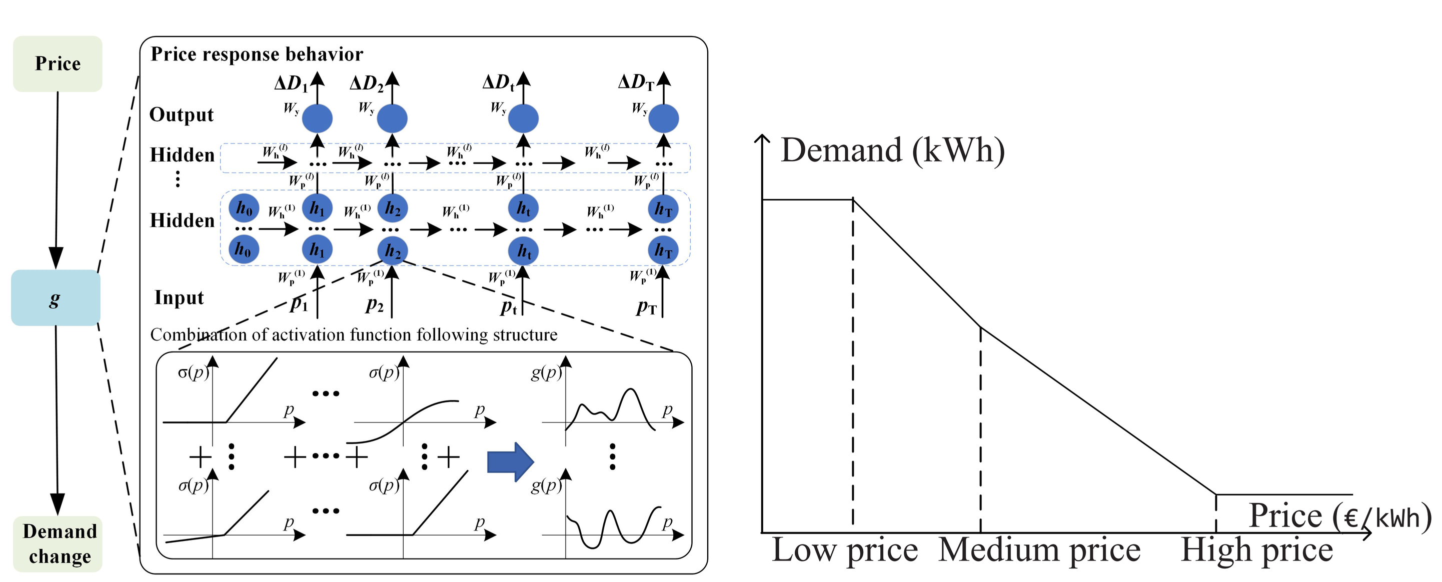
$$\min \|(D_{i,t}\pi_{i,t}/I_i - E_{\text{ave},t})\|,\ \forall i \in N_{\text{low}} \tag{1}$$

$$\text{s.t.} \sum_{i\in N} D_{i,t} \le \alpha_t * \sum_{i\in N} D_{i,t,0}, \forall t \in T \tag{2}$$

$$E_{i,t} \le \theta E_{\text{ini},t},\ \sum_{i\in N} \pi_{i,t} D_{i,t} \ge P_{\text{ini},t} \forall t \in T \tag{3}$$

$$D_i = G_i(\pi_i) \tag{4}$$

Here we use **machine learning method** and **mix-integer method** to formulate consumers' price response behavior G_i as Fig. 1 shows.



(a) Machine larning model (b) Mix-integer model

Figure 1. Modeling consumers' price responses behaviors.

The price response function is high dimensional non-liner or mix-integer, and the model is subject to operators' revenue recovery and demand reduction constraints.

Dataset

The mix-integer method utilizes the Low Carbon London (LCL) and Commission for Energy Regulation (CER) Smart Metering dataset to analyze consumer price response behaviors under time of use (ToU) tariffs. On the other hand, the machine learning method involves constructing an agent model to simulate consumer price response behaviors under time-varying pricing tariffs, with baseline data sourced from Pecanstreet. DR target is set as 2%.

Saturation Effects

We first show the saturation effects **using the mix-integer method** by comparing our approach with linear conditions.

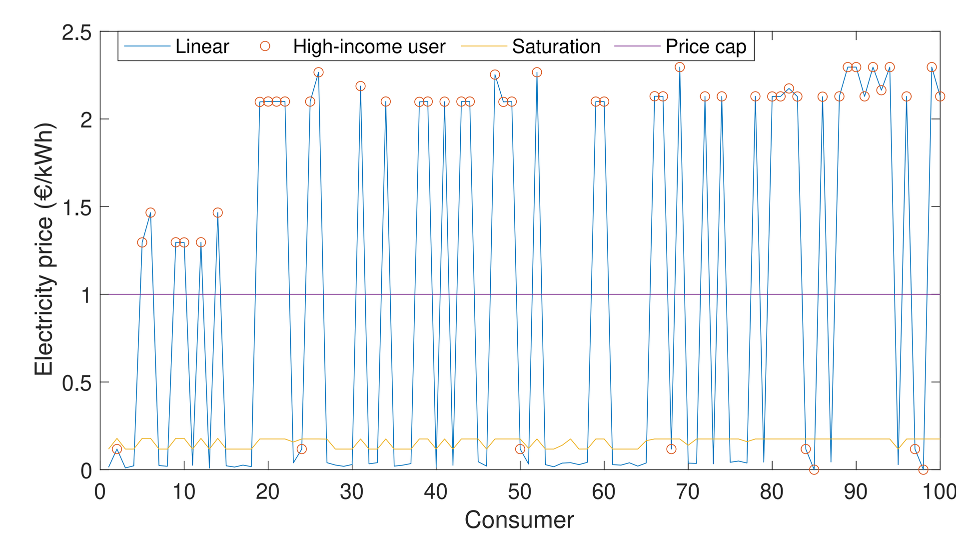
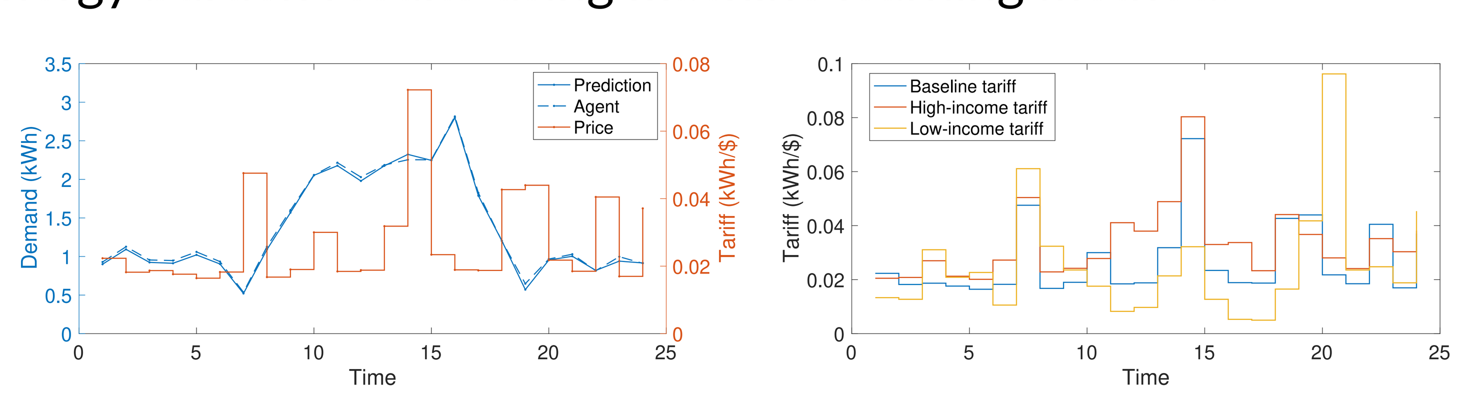


Figure 2. Comparison of tariffs.

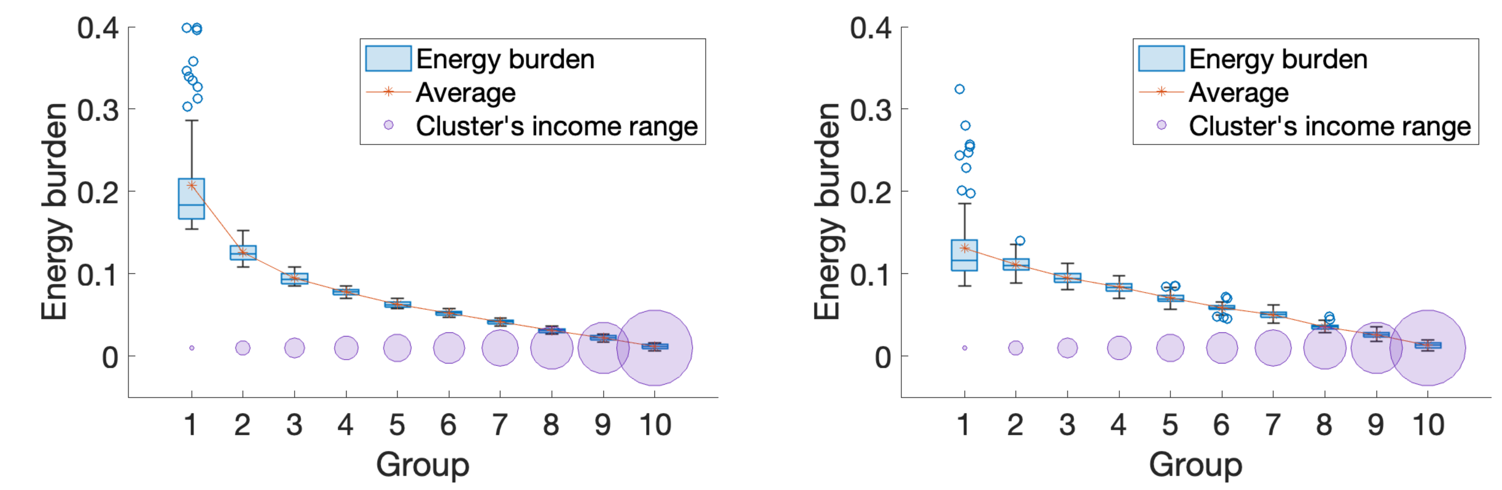
- The linear condition results in high tariffs for high-income consumers, surpassing price caps and becoming unrealistic.
- **Operators will benefit more by setting tariffs without considering the saturation effect**, resulting in additional costs for consumers.
- Thus we need to consider consumers saturation effects and individual response behaviors to design specific tariffs.

Equity Tariff Results

We then show identification effect, time-varying equity tariffs, and energy burden results using machine learning method.



(a) Learning results (b) Tariffs in low-income group and high-income group

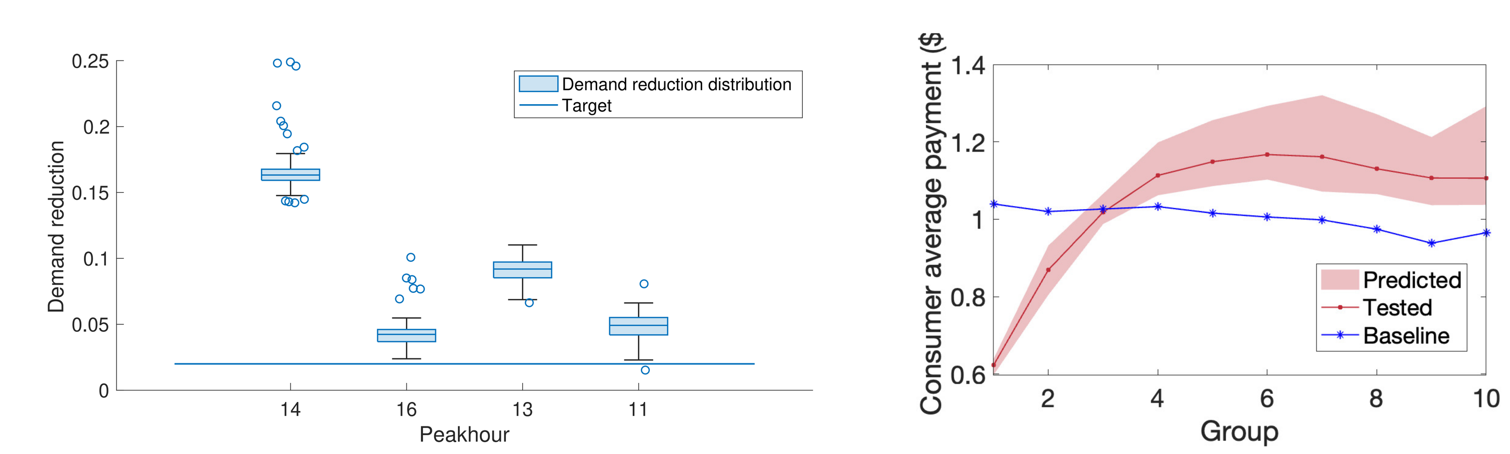


(a) Baseline tariff (b) Proposed tariff

Figure 4. Consumers' energy burden under different tariffs.

- Fig. 3 demonstrates that our method accurately captures consumer price response behavior. **Our tariffs are reduced for low-income consumers and increased for high-income consumers**, particularly during peak time slots.
- Both figures illustrate how **our method addresses energy inequity by implementing tiered tariffs for high- and low-income consumers**. This helps **redistribute the energy burden among consumers and provides protection to low-income consumers during DR events**.

To validate the DR effect of the proposed tariffs, we compare the agent model results with the identification results obtained through machine learning prediction.



(a) Demand reduction effect (b) Consumers' payment

Figure 5. Model validation with consumers' individual agent model.

- The peak demand reduction targets can be achieved with minor variations.
- The average consumer payment further attests to the reliability of our method. It shows **minor variation among consumers at different income levels**, which is reasonable and beneficial for all individuals.

The data and code used in this study is available from the authors upon reasonable request.

References

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