Personalized Price Design in Retail Market using Smart Meter Data

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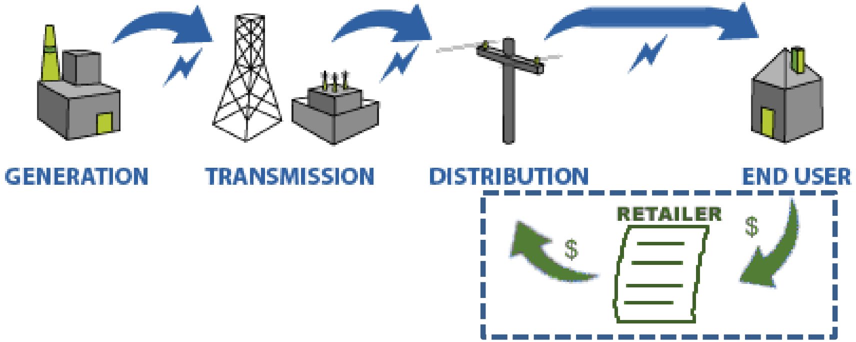
Outline

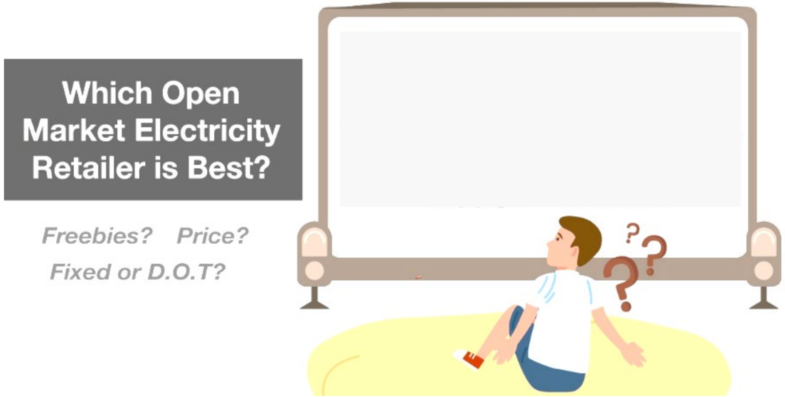
- ❑ Background
- ❑ Problem formulation
- ❑ Solution method
- ❑ Case studies
- ❑ Conclusions

Background

- ➢ The opening of electricity retailing market



- ➢ The need for diversified service

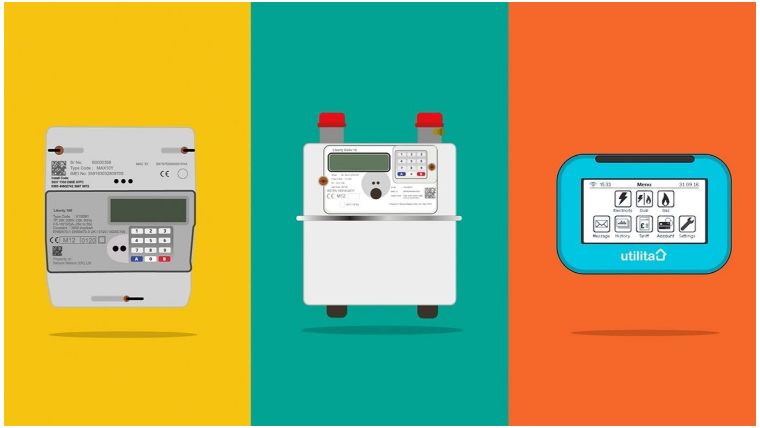


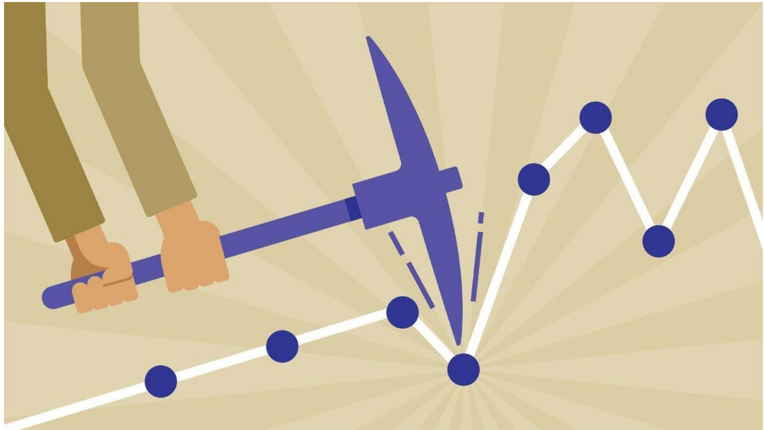
Challenge 1:

How to provide **diversified services** for different consumers to enhance the competitiveness of the retailers?

Background

- The deployment of smart meter device
- Provide massive fine-grained consumption data





UK: 2.9M   US: 70M   China: 96M

Challenge 2:

How to **uncover the value** of the massive smart meter data to provide better server to consumers?

Background

- Consumers choose freely in market

- Will consumers in the retail market act as the retailer expects?
- Are consumers given right incentive to act truthfully and faithfully?
- Is it appropriate to put every consumer different price?

Challenge 3:

How to predict the process of **self-selection** in a real market and how to give consumers **proper incentives**?

Backgrounds

Core idea & Main contribution

- ❖ ***Data-driven price design.*** Smart meter data contains great value which may help retailing price design.
- ❖ ***Respect self-selection.*** Consumers' willingness and rights to choose must be respected.

x No "hard" price designation for consumers.

x No experience-based pre-assumption on consumer' type.

Problem formulation

Challenges

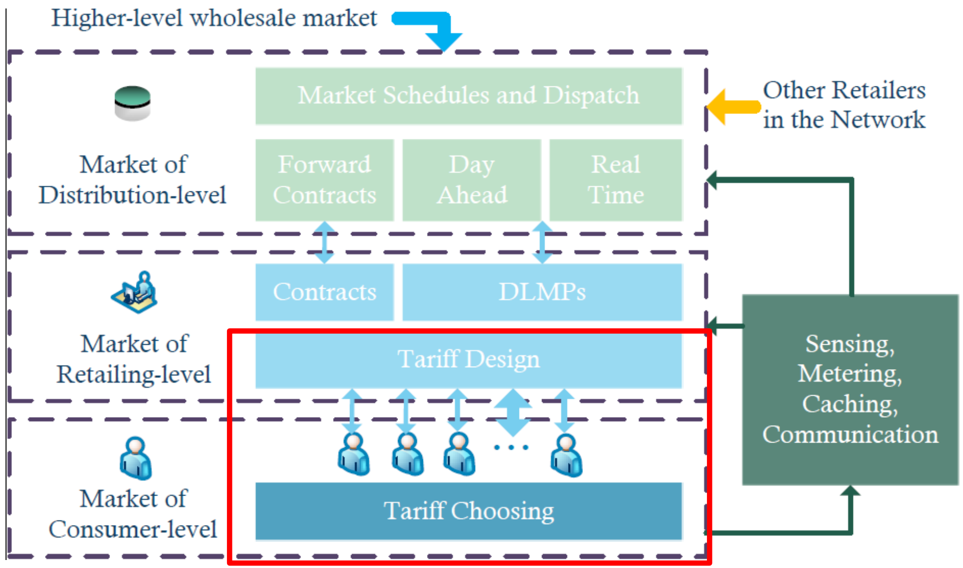
- Diversified service
- Mine consumers' inner need
- Satisfying consumers
- Self-selection in a real market
- Proper incentive

Data-driven price design

Compatible incentive design

Discover utility from data → Cluster load profiling data → Correlate preference with shape → Make centroids representatives → Form optimization problem

Problem formulation



Leader——Retailer

- Design pricing scheme
- Predict consumer behaviors

A Stackelberg game

Follower——Consumers

- Choose pricing scheme
- Adapt electricity consumption

Problem formulation - consumer

Consumer Utility

- Measure satisfaction
- Comparison between different plans
- Diminishing marginal utility

$$F(\boldsymbol{p},\boldsymbol{q}) = u(\boldsymbol{q}) - \sum_{t=1}^{T} p_t q_t$$

Consumer Strategy

- Strategic and rational consumers:

Utility Maximization

$$\boldsymbol{q}^*(\boldsymbol{p}) = \arg\max_{\boldsymbol{q}} \{F(\boldsymbol{p},\boldsymbol{q})\}$$

$$U(\boldsymbol{p}) = \max_{\boldsymbol{q}} \{F(\boldsymbol{p},\boldsymbol{q})\} = F(\boldsymbol{p},\boldsymbol{q}^*(\boldsymbol{p}))$$

How can smart meter data be useful?

$$F(\boldsymbol{p}_{(0)},\boldsymbol{q}_{(0)}) = 0 \qquad \frac{\partial F(\boldsymbol{p}_{(0)},\boldsymbol{q}_{(0)})}{\partial q_t} = 0, \quad \forall t$$

Original electricity consumption is the realization of Utility Maximization!

Problem formulation - incentive

Compatible incentive

If the retailer wants consumer k to choose pricing scheme r, the retailer **must guarantee choosing r is consumer k's dominant strategy**

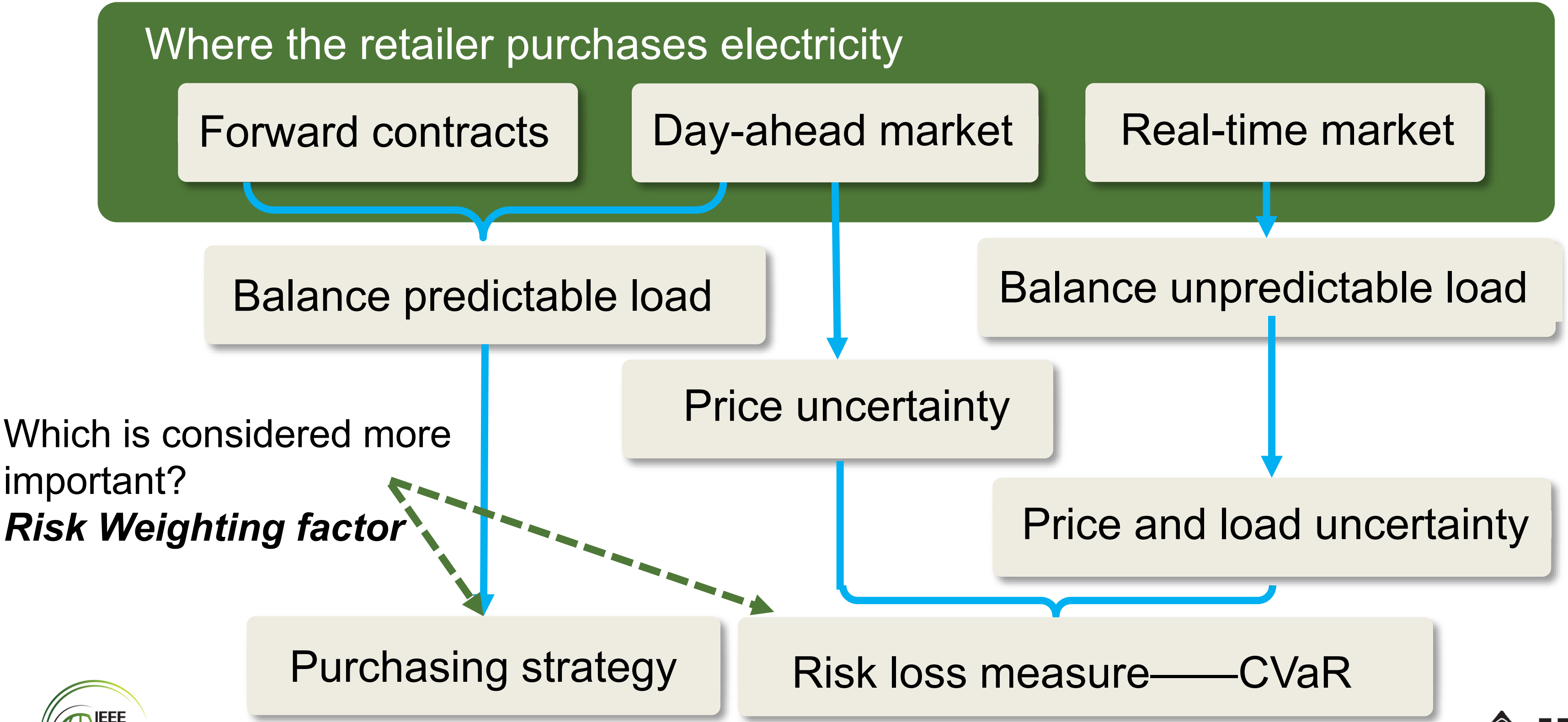
$$U_k(\boldsymbol{p}_r) \geq U_k(\boldsymbol{p}') \quad \forall k$$

Individual rationality

If the retailer wants consumer k to choose new pricing scheme r, the retailer **must guarantee choosing r is at least as good as previous situation**

$$U_k(\boldsymbol{p}_r) \geq U_k(\boldsymbol{p}_0) \quad \forall k$$

Problem formulation - retailer



Problem formulation - clustering

Why clustering?

Putting every consumer a different pricing scheme is not appropriate. ***Offering a few choices and letting consumers select*** *is much better.*

Thus clustering is needed to cluster consumers.

- **Consumers' willingness.** Facing too many choices reduce consumers' willingness to participate in retailing market.
- **Social Welfare.** Putting every consumer a different pricing scheme is a kind of perfect price discrimination which reduces consumer welfare.
- **Engineering practicability.** Problem will become unacceptably complex as the number of consumers rises.

Problem formulation - clustering

Different Clustering Methods

- Hierarchical Clustering
- *K*-means
- Fuzzy C-means
- Gaussian mixture

One method may not fit all data sets

Clustering evaluation

Davies Bouldin Index

With-cluster compactness

Between-cluster seperation

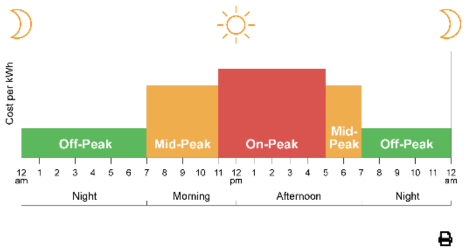
Centroid as representative

Problem formulation – optimization framework

Optimization framework – a MINLP model

- Objective： Retailing profit maximization
- Constraints：
  - Load balance
  - Consumer reaction
  - Compatible incentive
  - Risk measure CVaR
  - Price structure: Various choices

- Price category： CPP RTP ToU



Lower Risk
Less changes

Problem formulation – optimization framework

Optimization framework – a MINLP model

- Objective：Retailing profit maximization

$$\max\ R = \sum_{r=1}^{R}\sum_{t=1}^{T} K_r \times p_{k,t} \times q_{k,t} - \sum_{t=1}^{T}\sum_{n=1}^{N_F} p_n^F \times L_n^F \times o_{n,t}^F \times o_n - \sum_{t=1}^{T} p_t^{D,est} \times L_t^D - \xi \times CVaR$$

Consumer payment　Forward contracts　DA　Risk Loss in DA & RT

- Constraints：Predictable load balance

$$\sum_{r=1}^{R} K_r \times q_{r,t} = \sum_{n=1}^{N_F} L_n^F \times o_{n,t}^F \times o_n + L_t^D,\ \forall t$$

Consumer load　Forward contracts　DA

DA=Day-ahead market, RT= Real-time market

* nonlinear terms are marked in red

Problem formulation – optimization framework

Optimization framework – a MINLP model

- Constraints： Compatible incentive

$$U_r(\boldsymbol{p}_r) \geq U_r(\boldsymbol{p}') \quad \forall k$$

Choosing $\boldsymbol{p}_r$ is consumer k's dominant strategy, k likes $\boldsymbol{p}_r$ than any other pricing schemes

$$U_r(\boldsymbol{p}_r) \geq U_r(\boldsymbol{p}_0) \quad \forall k$$

Choosing $\boldsymbol{p}_r$ is consumer k's rational choice, k likes $\boldsymbol{p}_r$ than the old pricing schemes

- Constraints： Utility and response

$$q_t = \left(\frac{p_t}{p_{t(0)}}\right)^{\frac{1}{\alpha-1}} \times q_{t(0)}$$

Reactions

$$U(\boldsymbol{p}) = \sum_{t=1}^{T}\left(\frac{1}{\alpha}-1\right)\left[\left(\frac{p_t}{p_{t(0)}}\right)^{\frac{\alpha}{\alpha-1}}-1\right] \times q_{t(0)}\, p_{t(0)}$$

Utility

* nonlinear terms are marked in red

Problem formulation – optimization framework

Optimization framework – a MINLP model

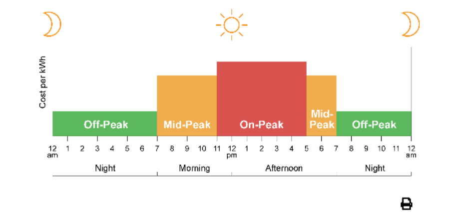
- Constraints： Risk measure CVaR

Loss in DA Loss in RT

$$CVaR = \inf_{a \in R}\{a + \frac{1}{(1-\alpha^{CVaR})\cdot N_S}\sum_{n_s=1}^{N_s}[(-\Delta R^D - \Delta R^{RT}) - a]^+\}$$

- Constraints： Price structure

Price category: CPP RTP $\boxed{\text{ToU}}$



Lower Risk
Less changes

$$\sum_{m=1}^{M} e_{r,t}^m = 1, \qquad \sum_{t=1}^{T} e_{r,t}^m \geq D_{\min}, \ \forall m,r$$

$$|e_{r,T}^m - e_{r,1}^m| + \sum_{t=2}^{T} |e_{r,t-1}^m - e_{r,t}^m| = 2, \ \forall m,r$$

$$p_{r,t} = \sum_{m=1}^{M} e_{r,t}^m \times p_r^m, \quad \forall t,r$$

m block ToU

* nonlinear terms are marked in red

DA=Day-ahead market, RT= Real-time market

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Solution method

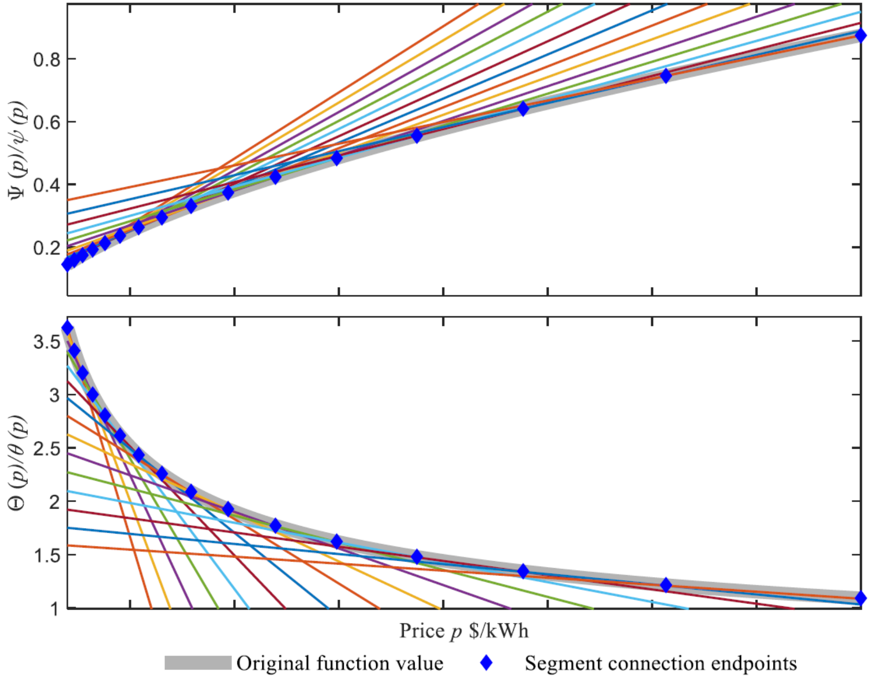
Nonlinear model

- Power exponent $p_{r,t}^{\frac{\alpha}{\alpha-1}}$, $p_{r,t}^{\frac{1}{\alpha-1}}$
- Two variables' product $p_{r,t} \times q_{r,t}$

Linear model

- Linear segment approximation

  Take $p_{r,t} \times q_{r,t}$ as a whole



Solution method

Nonlinear model

- Binary variables times continuous variables
- Absolute value $|e^m_{r,t-1} - e^m_{r,t}|$
- CVaR

Linear model

- Add auxiliary variables

Conversed to linear equations

$$\sigma_{r,t} \le M \times e^m_{t,r}$$
$$\sigma_{r,t} \le p^m_r$$
$$\sigma_{r,t} \ge p^m_r - M \times (1 - e^m_{t,r})$$
$$\sigma_{r,t} \ge 0$$

$$e_1 - e_2 \le A \le e_1 - e_2 + 2 \times B$$
$$e_2 - e_1 \le A \le e_2 - e_1 + 2 \times (1 - B)$$

$$CVaR \ge a + \frac{1}{(1-\alpha^{CVaR}) \cdot N_S} \sum_{n_S=1}^{N_S} W_{n_S}$$
$$W_{n_S} \ge 0$$
$$W_{n_S} \ge [(-\Delta R^D_{n_S} - \Delta R^{RT}_{n_S}) - a]$$

* new variables are marked in blue

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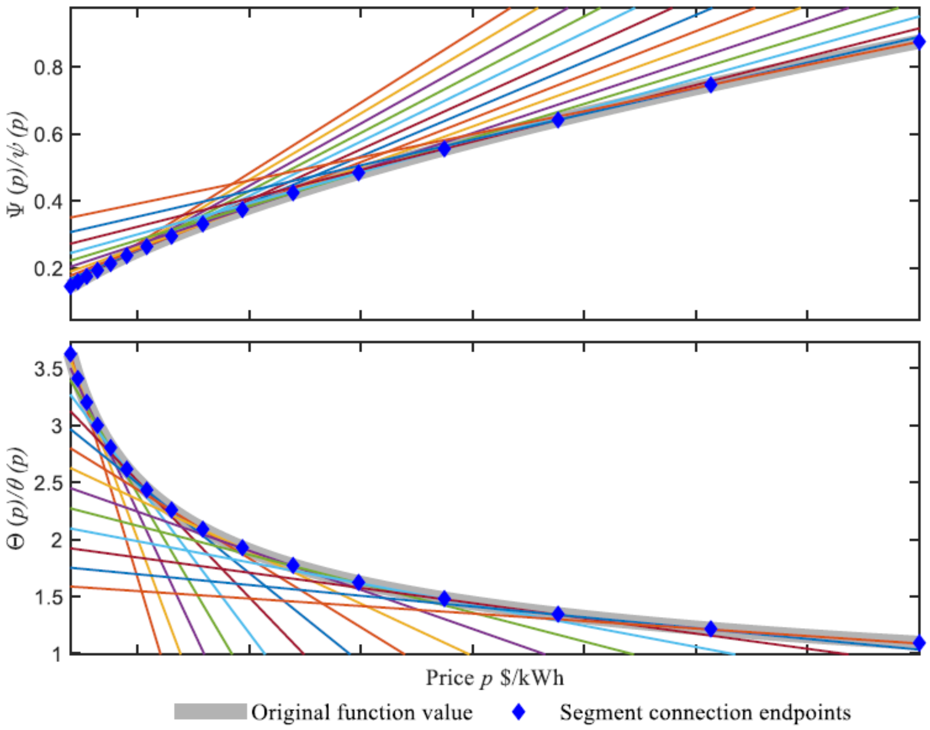
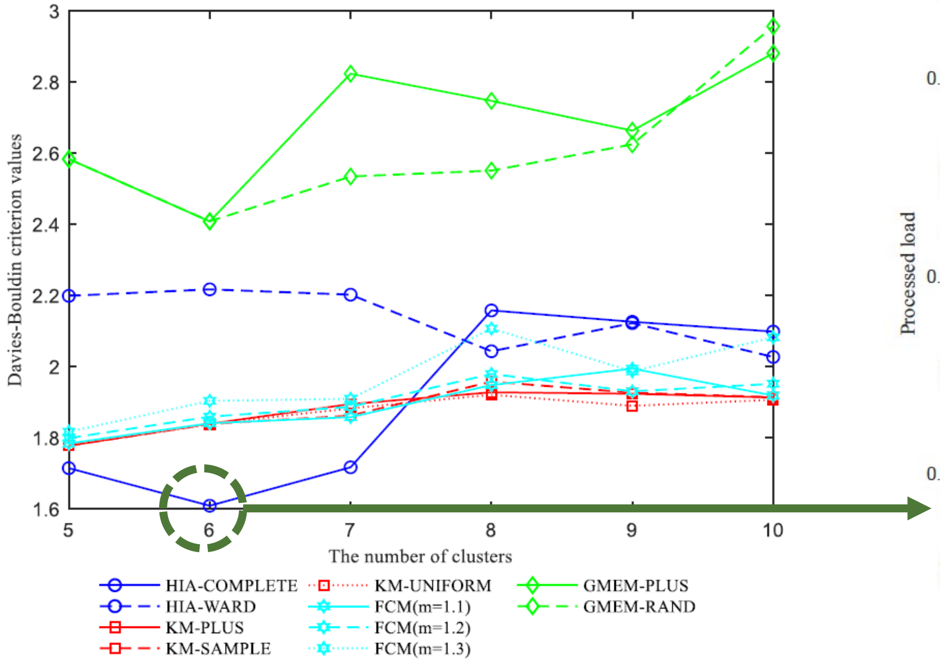
Case Study

The smart meter electricity trial data of 6435 consumers from Commission for Energy Regulation (CER) based in Ireland are used for case study. The data were collected every 30 minutes.

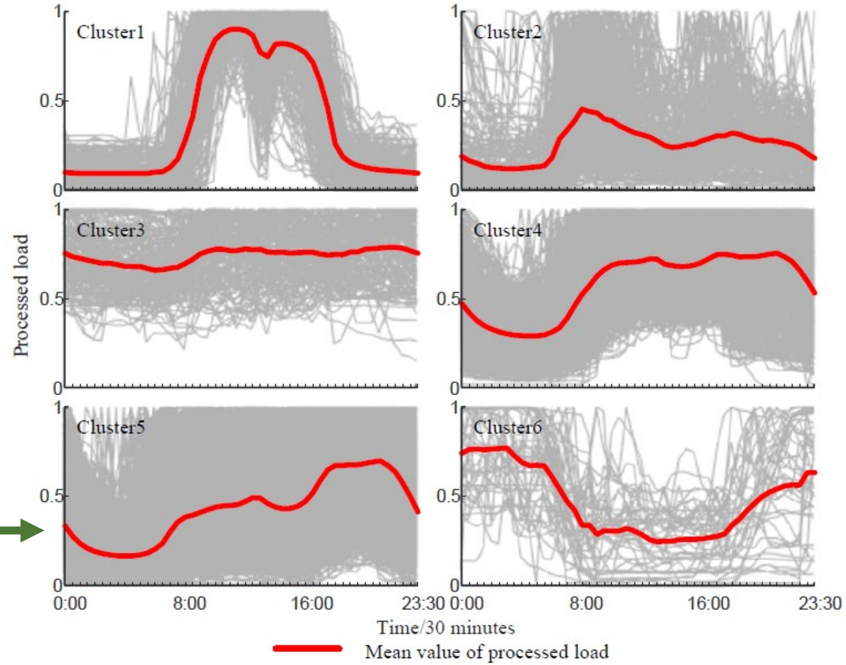


Linear segment approximation(12 segments)

Case Study - clustering

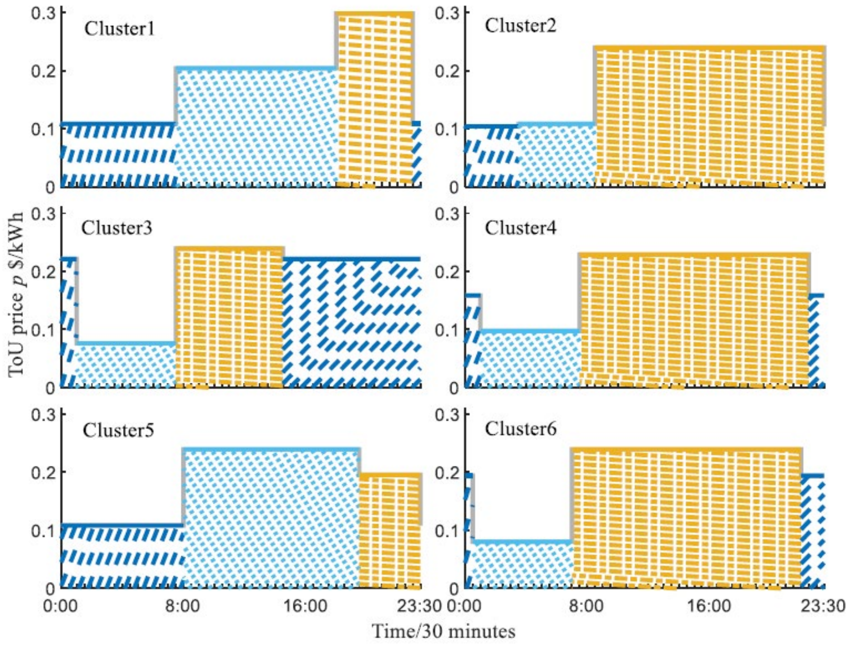


DB index result

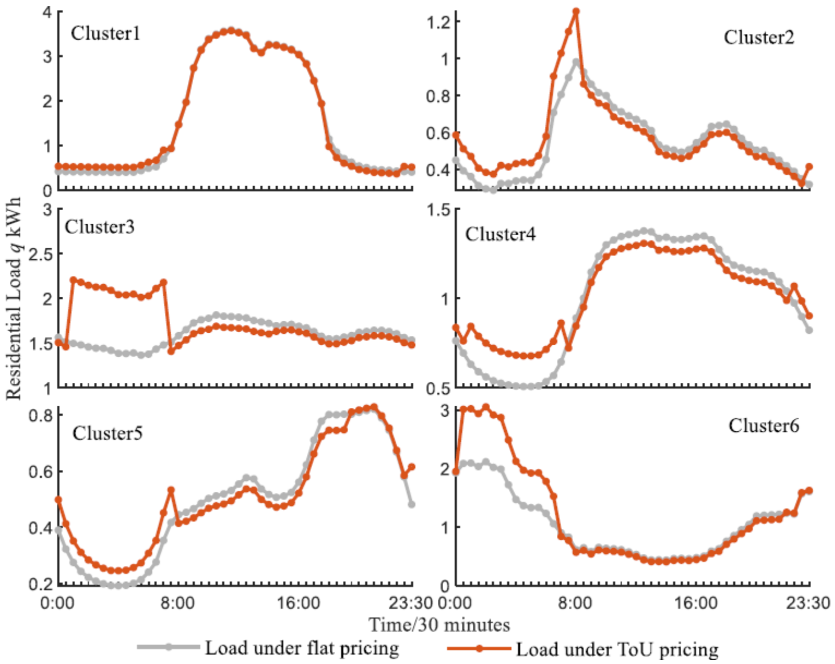


Clustering result

Case Study – price and reactions

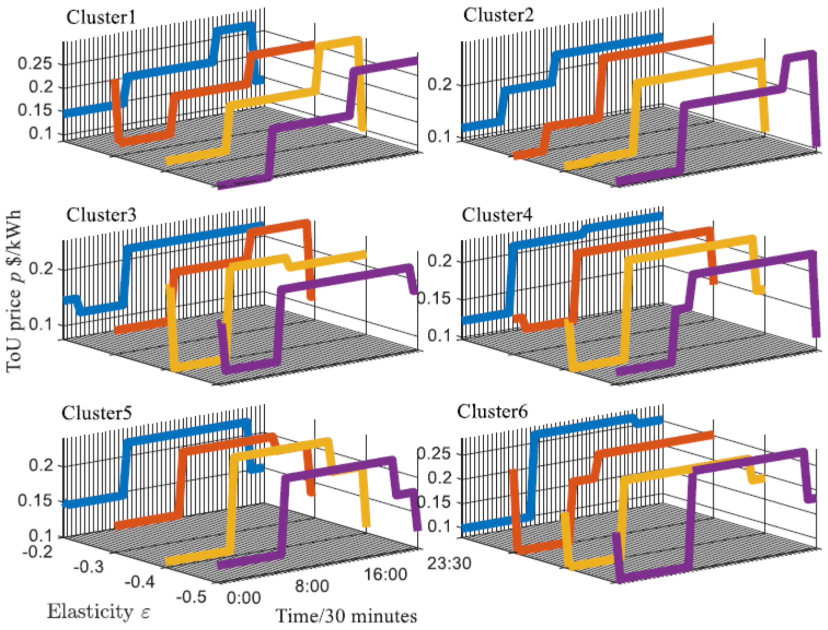


Personalized price

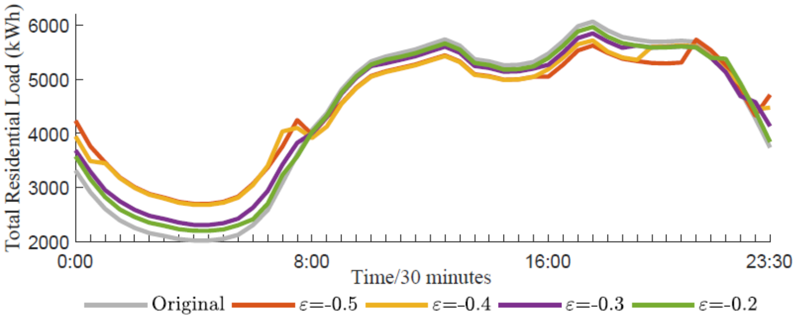


Consumer response

Case Study – sensitivity analysis on elasticity



ToU under different elasticity



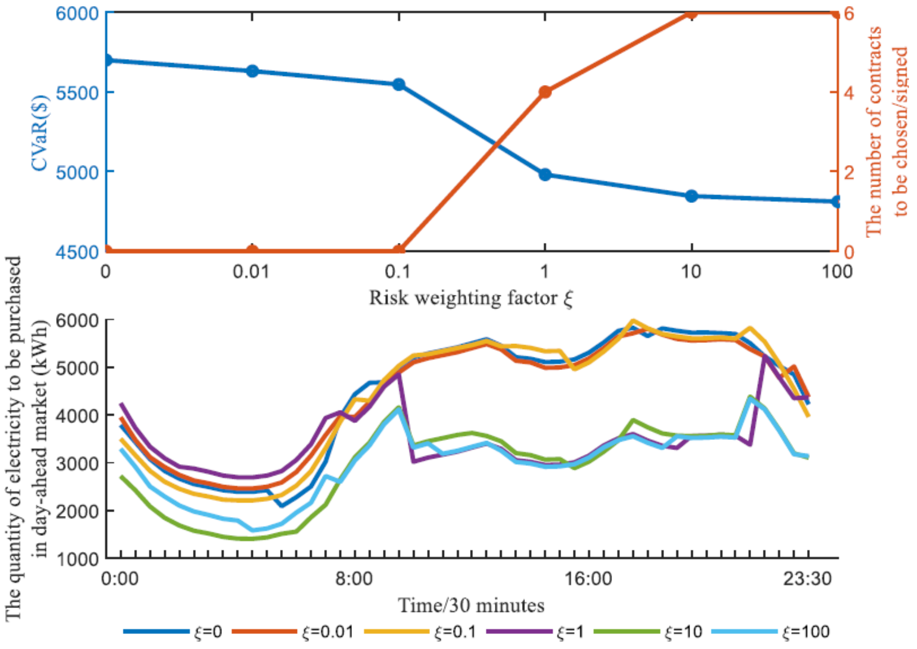
Total load under different elasticity

Retailing profit under different elasticity

Elasticity	Original	-0.2	-0.3	-0.4	-0.5
Retailing Profit($)	752	833	977	1186	1385

Elasticity ↓ 😢 Willingness to change ↓

Case Study – sensitivity analysis on risk weighting factor



How **CVaR, the quantity of power bought from day-ahead market and through forward contracts** changes with the change of risk weighting factor?

risk weighting factor rises ↑

attach more importance to risk ↑

minimize CVaR ↓

buy less from day-ahead market ↓

buy more through forward contracts ↑

Case Study - sensitivity analysis on clustering methods

How do different clustering methods affect the model from the angle of economy rather than just statistics?
Clustering may have errors but all the consumers' preferences as the corresponding cluster centroids' preferences. How well does the "representative" perform? ------ **Go back to individual situation to simulate**!

1. First, the utility gained from the six pricing schemes is calculated and sorted in ***descending order*** for every consumer.
2. Second, since consumers act in the principle of utility-maximization, **the top in the order for every consumer is the consumer's first choice** in real market. The proportion of consumers whose first choices are just the same as their corresponding centroids' choices is the index *First Choice*.
3. Third**, the second highest in the order for every consumer is the consumer's second choice** in real market. The proportion of consumers, one of whose first choices or second choices are just the same as their corresponding centroids' choices, is index *Second Choice.* Second Choice is calculated to extend differences tolerance between individuals and centroids.

Case Study - sensitivity analysis on clustering methods

	RP	SW	AP	F/SC
Original	752.03	0	0.2	-/-
HIA-COMP	**1186.01**	**339.72**	**0.1947**	**65%/89%**
HIA-WARD	1188.70	10.01	0.1971	33%/59%
KM-PLUS	1145.68	7.01	0.1973	9%/20%
KM-SAMPLE	1137.61	4.50	0.1975	22%/48%
KM-UNIFORM	1142.61	15.76	0.1973	11%/31%
FCM(m=1.1)	1150.43	9.43	0.1970	30%/47%
FCM(m=1.2)	1176.08	18.64	0.1968	19%/35%
FCM(m=1.3)	1208.06	0.64	0.1970	8%/20%
GMEM-PLUS	1145.82	36.01	0.1965	13%/28%
GMEM-RAND	1144.85	46.60	0.1967	10%/24%

How much profit does the retailer get?

- RP=Retaling Profit($)

How much welfare do the consumers get?

- SW=Social Welfare
- AP=Average Price($/kWh)

How well does clustering perform?

- F/SC=First/Second Choice

> - The most accurate prediction
> - The most profitable for consumers

Conclusions

- This paper proposes a data-driven approach to design ToU tariffs explicitly dealing with compatible incentive.
- The Stackelberg game between the retailer and the strategic consumers, the incentive-compatible market, the retailer's cost, risk and purchasing strategy are considered in this model.
- Case study results verify that the ToU tariff can contribute peak shaving, increasing the retailer's profitability, and ensuring consumers' willingness and preferences at the same time.

Question and Answer ?

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