Pricing Residential Electricity Using Smart Meter Data

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Motivation

- Demand side is becoming more distributed and more active
  - Solar
  - EV
- Customers are becoming more engaged
  - Demand response
- How do we engineer this system?

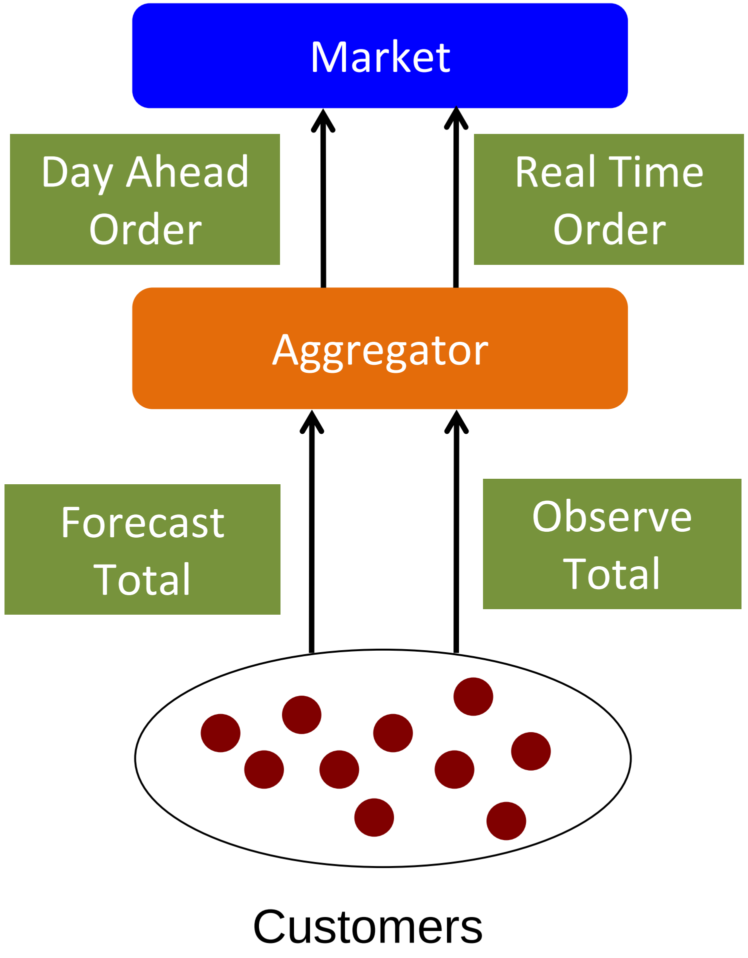
This talk: aggregate behavior from individual consumption data

Data Source

- Pacific Gas and Electric smart meter data
- Household level consumption at 15 minutes resolution
- Examples are from California
- Some general conclusions that should be applicable

Traditional Demand Structure

- Utilities purchase bulk energy
- Customers are offered fixed rates ($/kwh)
- Rate plans designed based on the aggregate consumption



Rate Design

- Rethinking of rate design
  - Time of use
  - Tiered
  - Real-time

- Retail Competition
  - ERCOT has 200+ plans people can choose from

How should we design rate plans that is efficient and stable?

Look at data!

Customized Plans

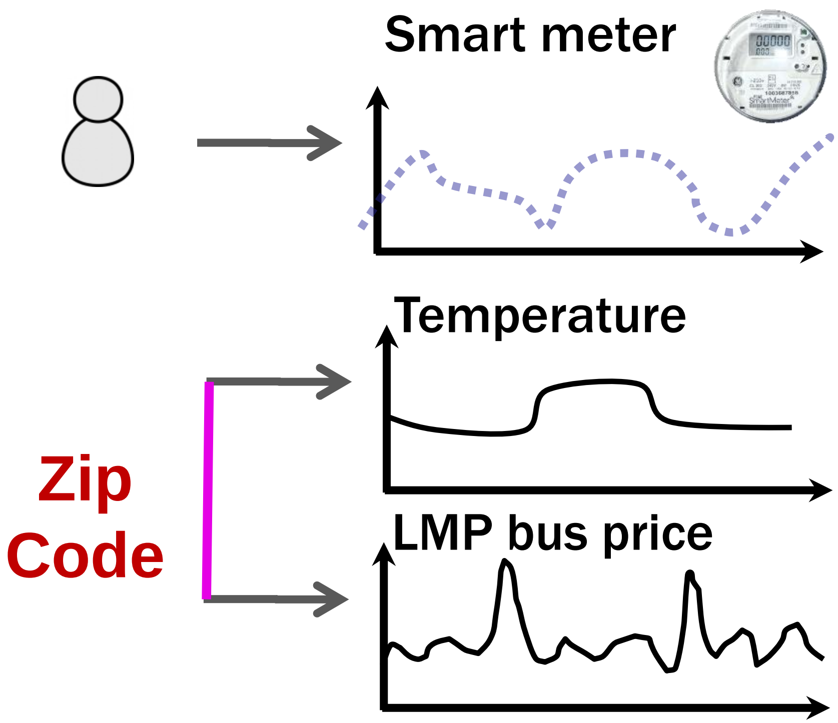
Understanding customer data

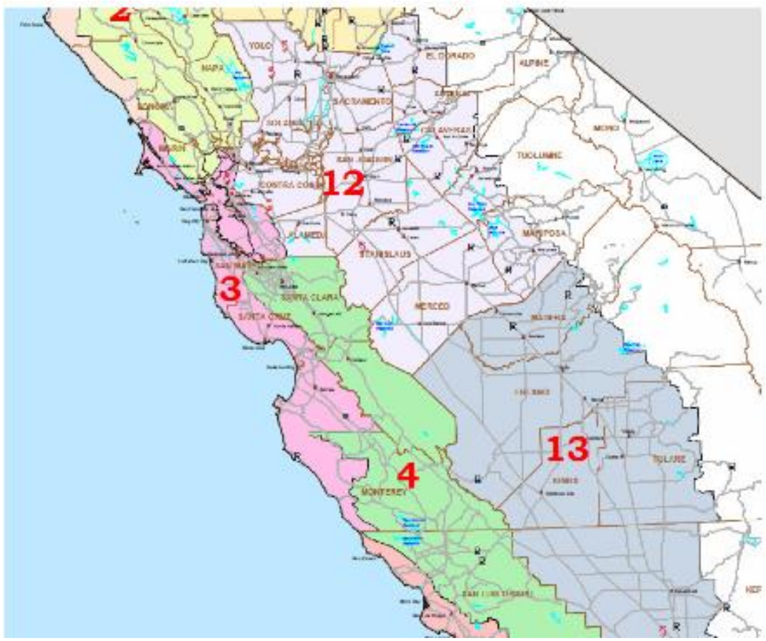
- Consumption patterns
- Forecasting

Building a rate plan design

- Revenue management
- Customer selection

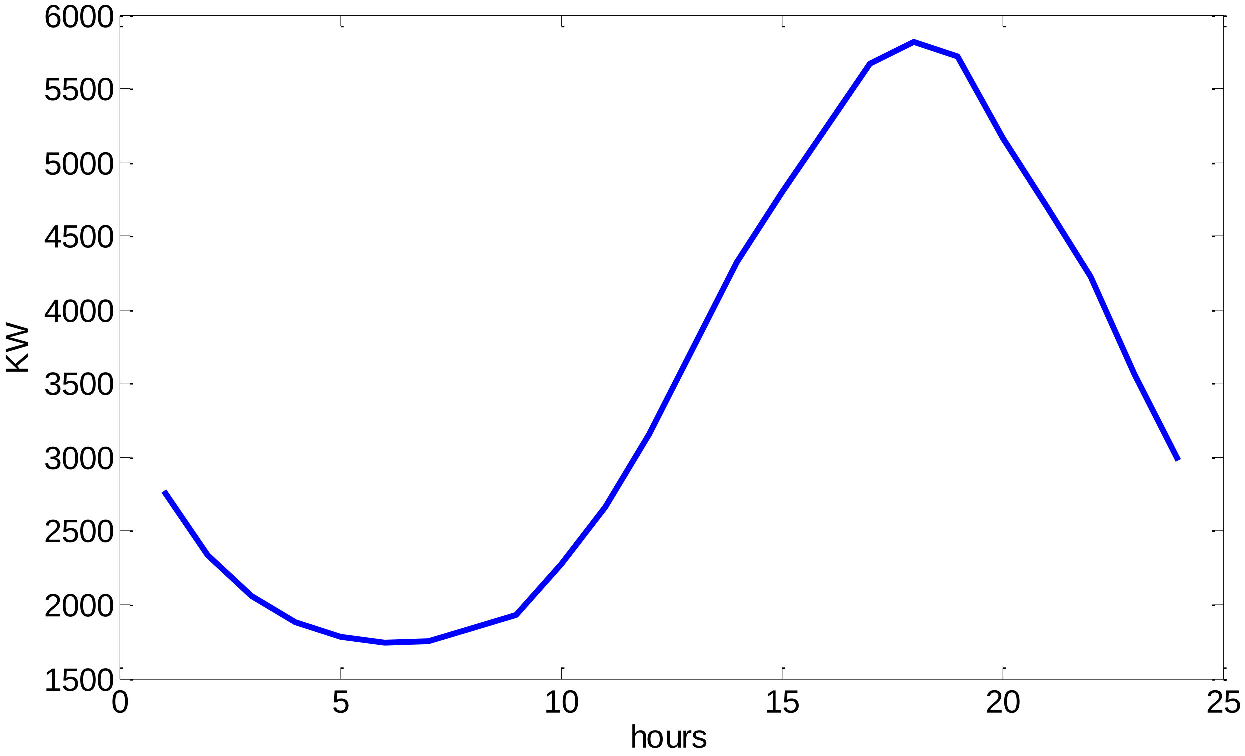
Data





Consumption Pattern

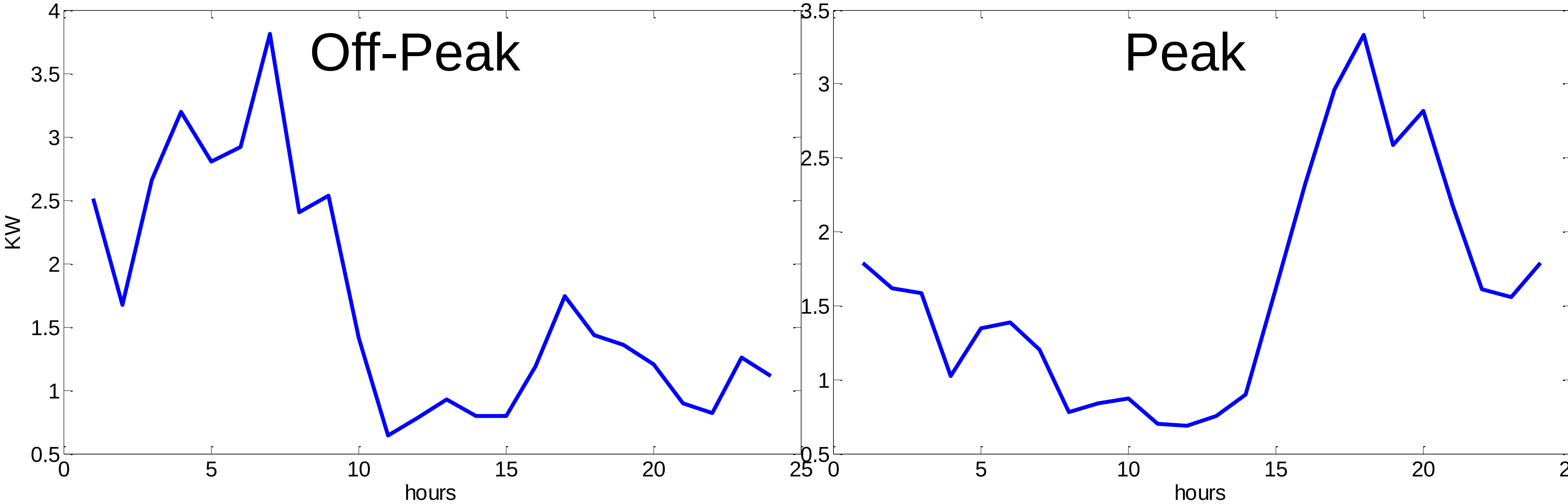
- Aggregate load (4 zip codes in CA)



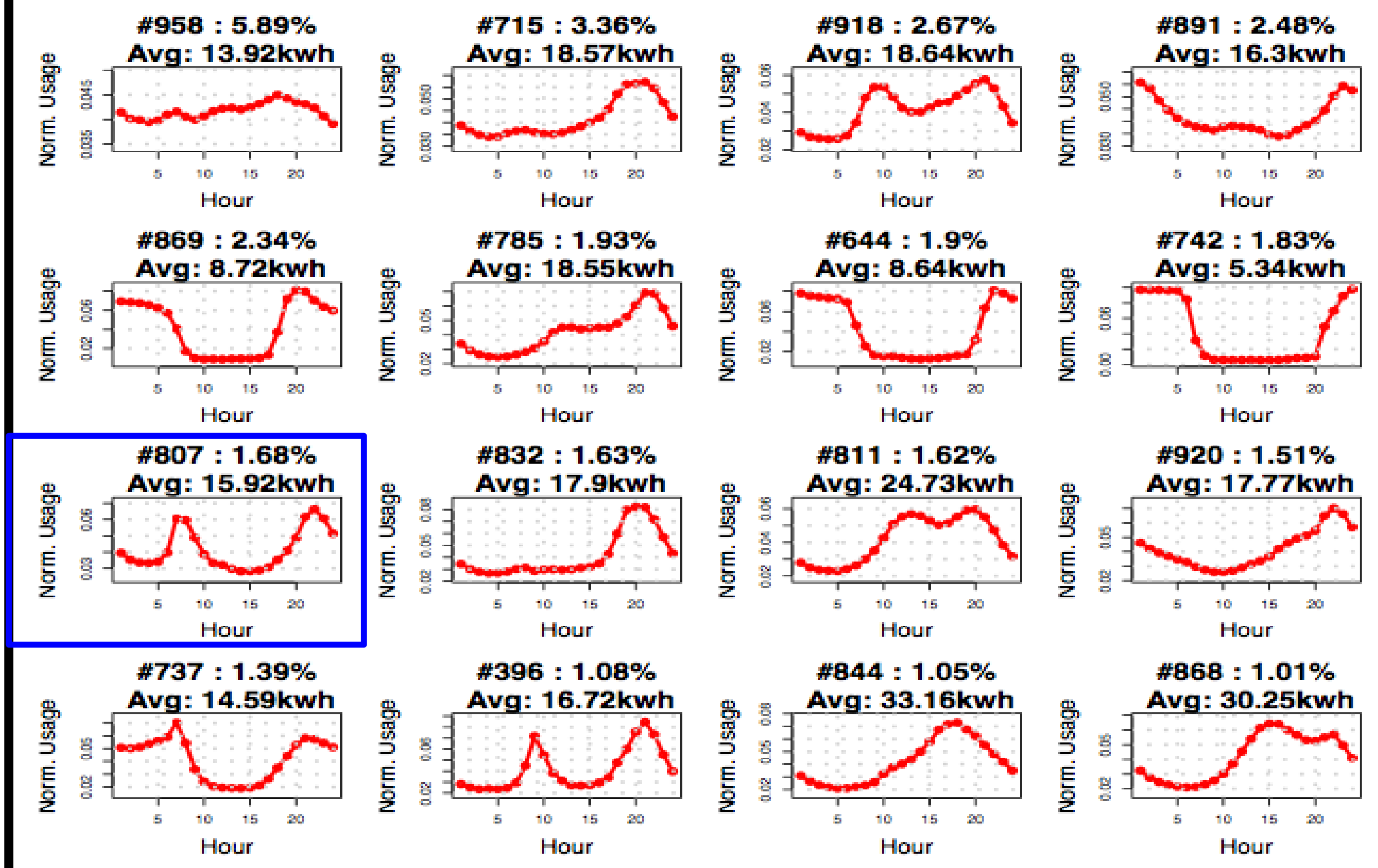
- What do individual profiles look like?

Individual Consumption Profiles

- Not everybody are the same



Consumption Patterns

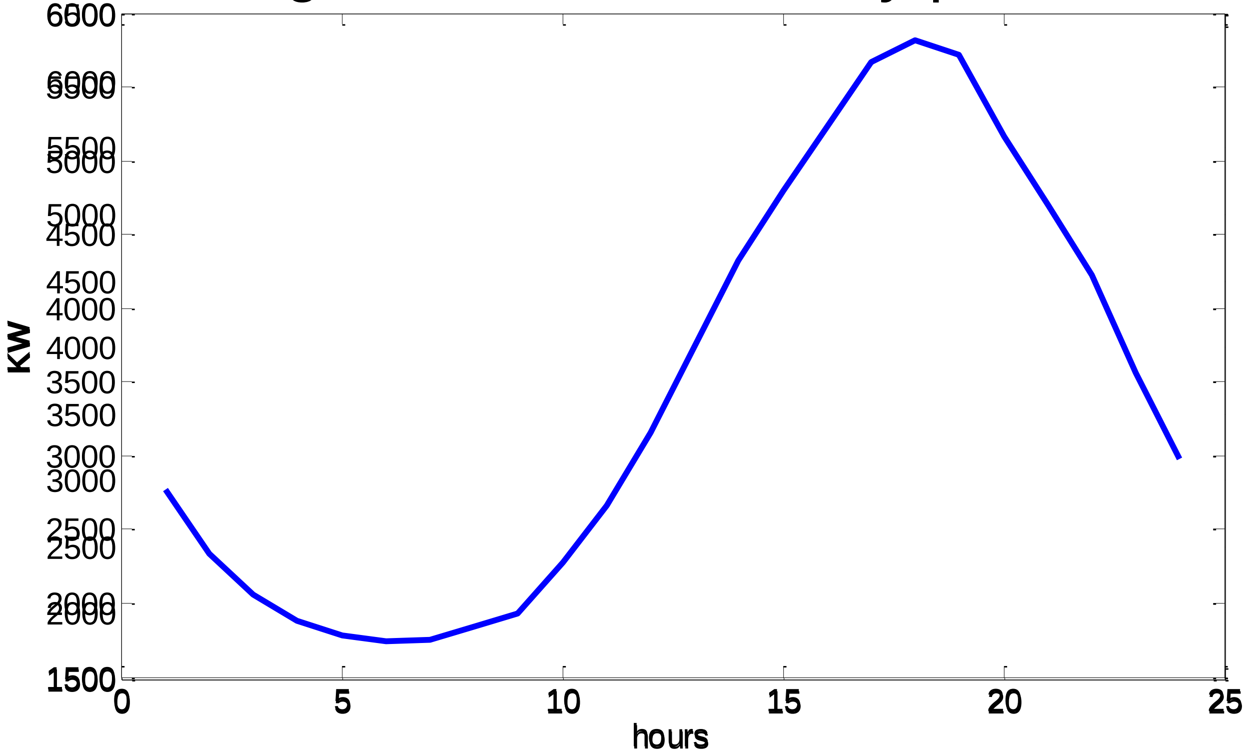


Residential Patterns

Aggregate Rate

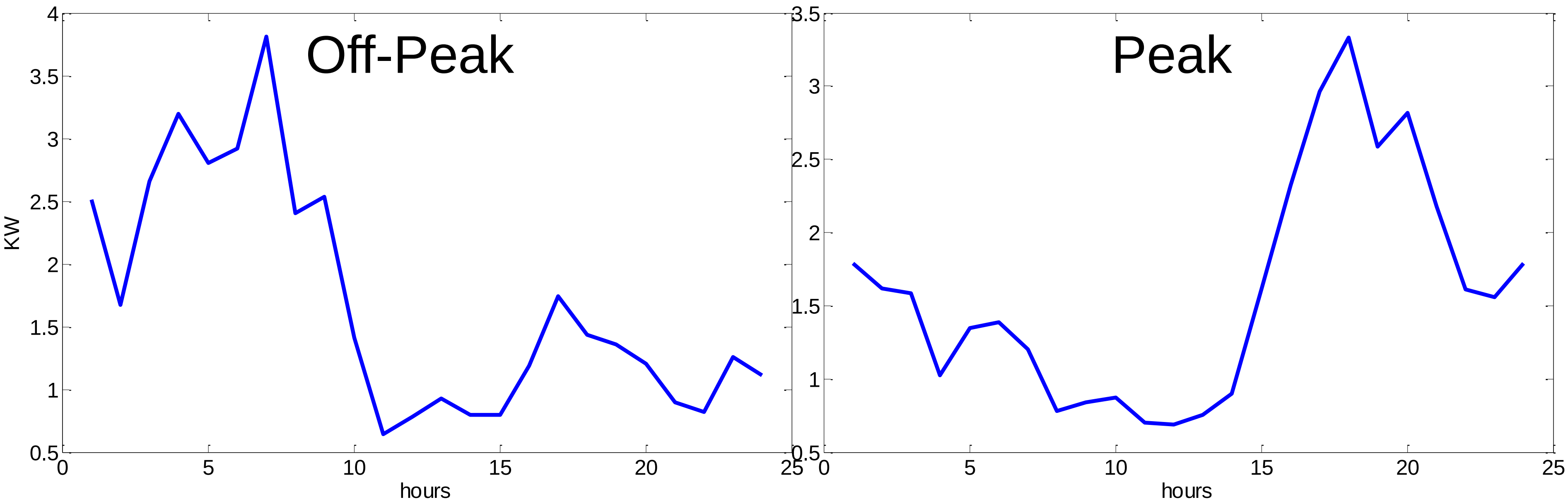
- Aggregate Consumption

Aligns with the electricity price



- Cost is shared equally among the users

Divide Users into Small Groups



- Cost Sharing

- Why not group “off-peak” households?

- More efficient to group users of similar profiles

Fixed Rate Design

Our proposal:

- Fixed rate for a group of customers: single $/kwh price
- Different groups gets different rates
- Find the right group

Zonal:

- Different zones with different prices

Time of Use:

- Prices varies by time of day

Real-time

- Changing rates

Individualized Rates

- Users should pay a rate that reflects their power usage

$$\text{rate} = \frac{\sum_{t=1}^{T} \text{price}_t \cdot \text{demand}_t}{\text{Total Demand}}$$

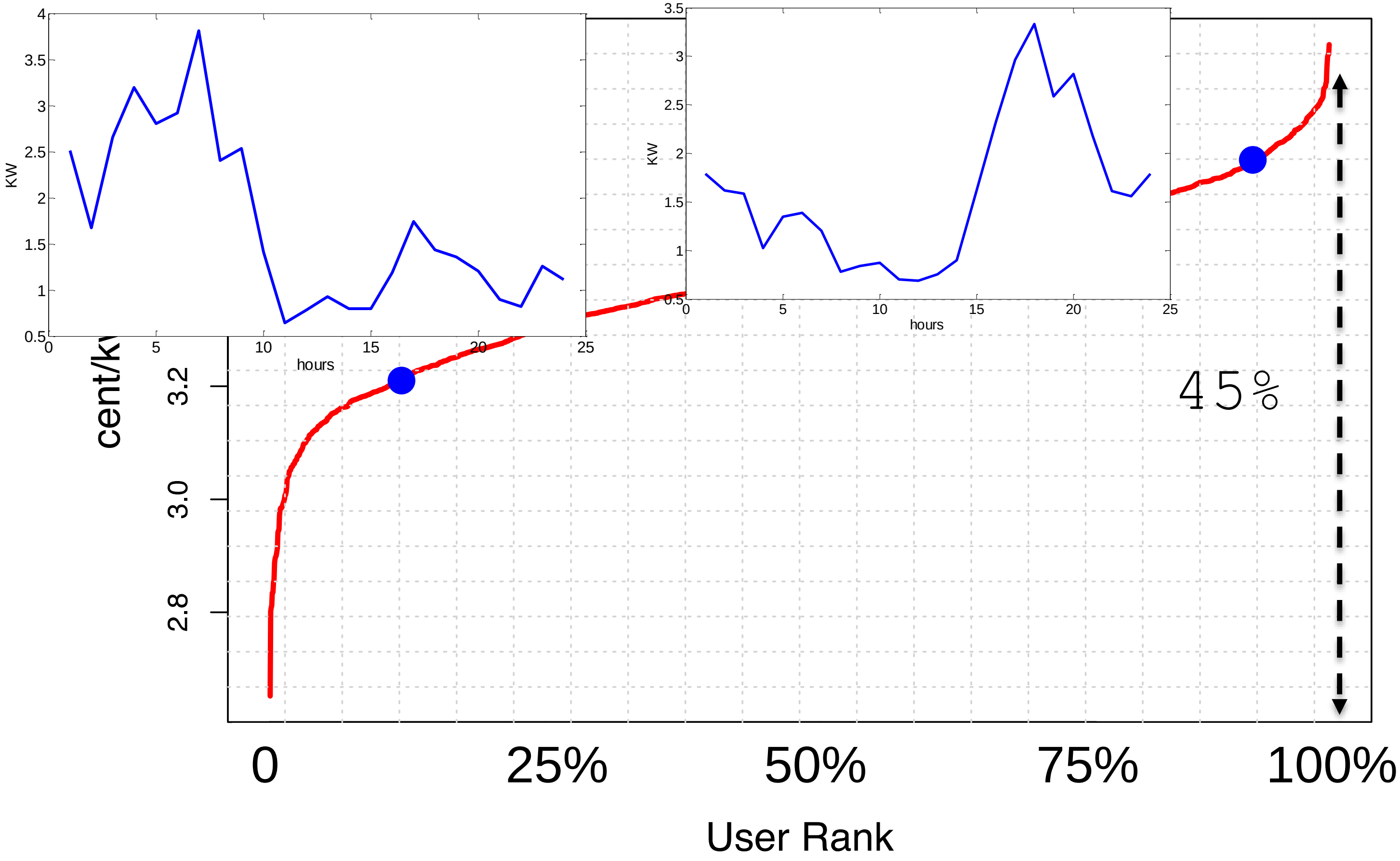
- Different users have different rates:

  Off-peak rates are lower than on-peak rates

- “Fair” design of rates

Ranking Users

- If consumption was exactly known and consistent



- No one has the same consumption pattern very day!

Uncertainties in Consumption

Argument for managing large groups of customers:

- Load can be forecasted
- Protect against real-time price spikes

Hourly forecast, day-ahead

- Single Household: 100%

- Substation Level: 2~3%

Day ahead forecasting

- Simple model: adaptive temperature driven AR for shape and total consumption

24 hour profile=total * normalized shape

Predict from historical load and temperature forecast

$$total_t = \alpha \cdot total_{t-1} + \beta \cdot Temp_t$$

$$shape_t = A \cdot shape_{t-1} + B \cdot Temp_t$$

Parameters are learned from data

Error

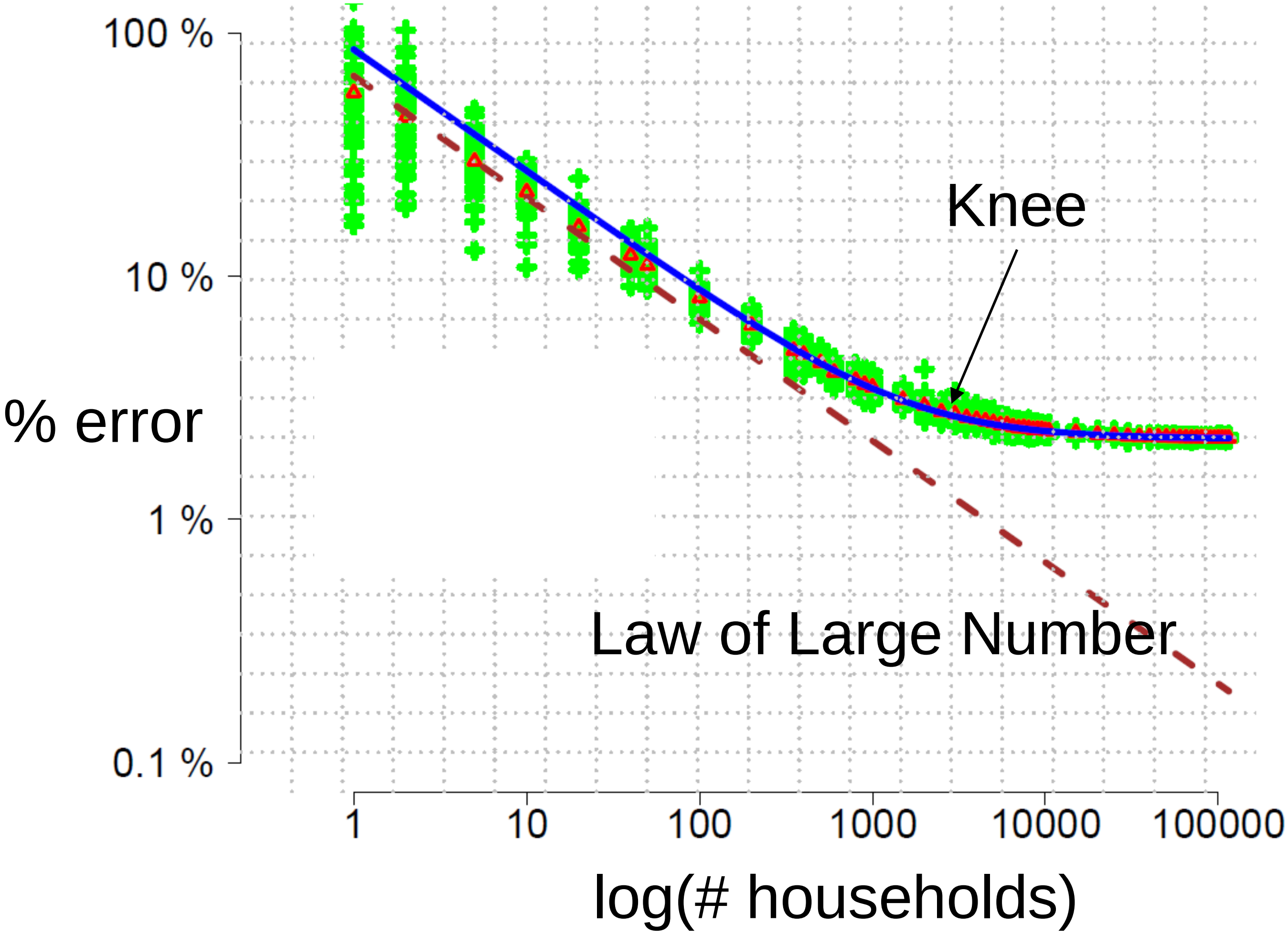
- We measure error by “coefficient of variation” (CV)

$$CV = \frac{\sigma}{\mu} = \frac{\text{Standard Deviation}}{\text{Mean}}$$

- Can be thought as the % error in forecasting
- Smaller the better
- Single household 100%
- 200,000 households 2%

Forecasting

- PG&E dataset, hourly smart meter data, 1 million households
- AR Model based on temperature



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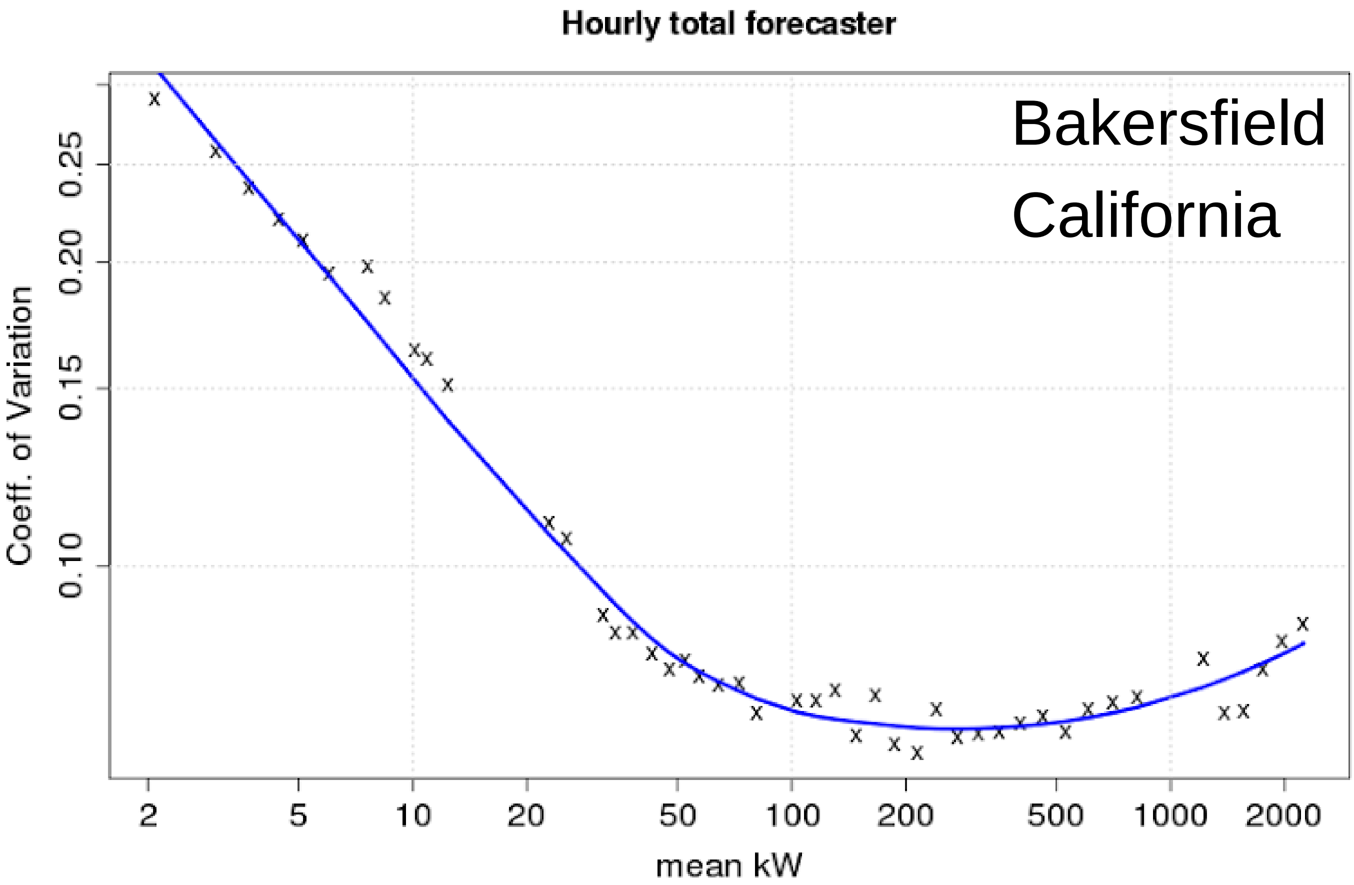
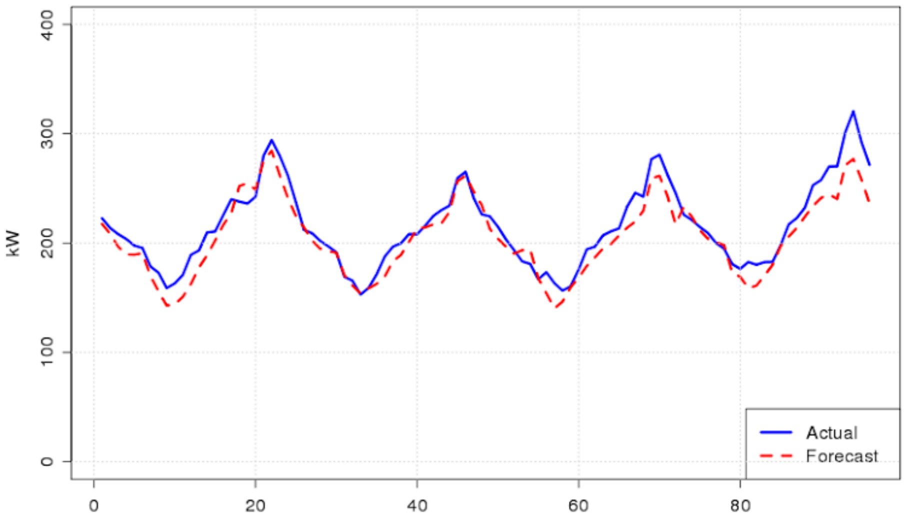


Forecast examples

Hourly predictions, group of ~200 kW



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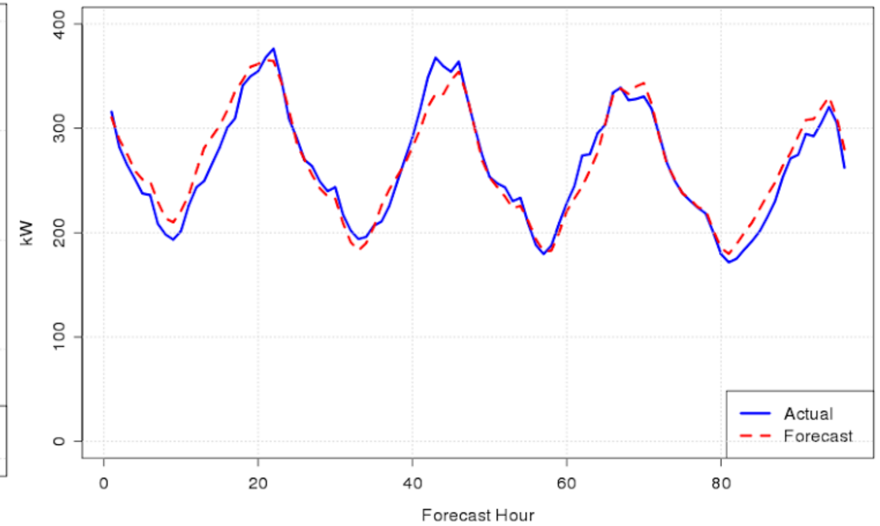
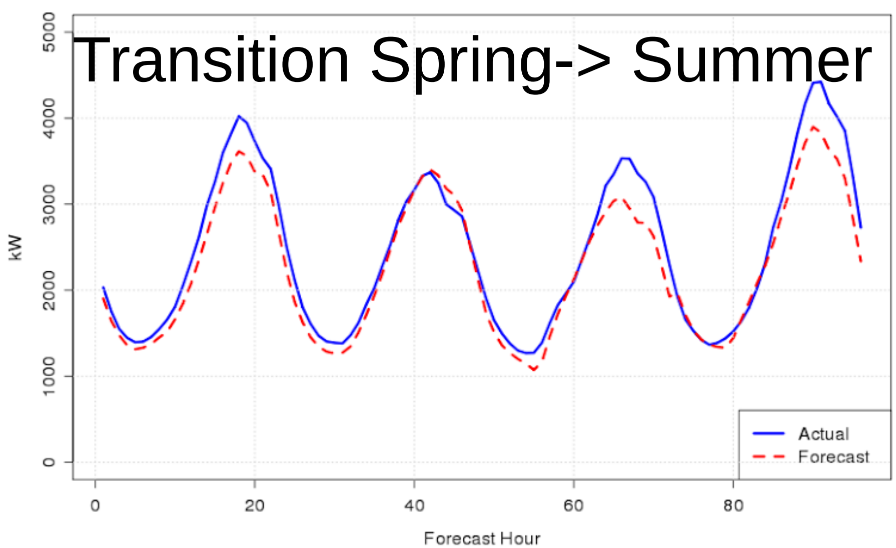


Hourly predictions, entire population



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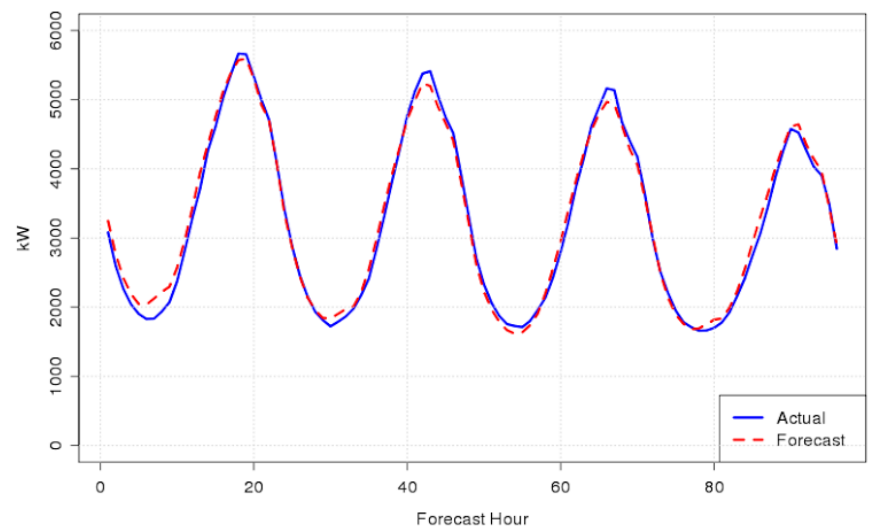


Forecasting Summary

- Small groups can be forecasted as accurately as very large aggregates
- No efficiency loss in considering smaller groups

Rate of a group:

- Find the aggregate consumption of that group
- Calculate the average cost for this group
- Divide the cost by energy use to get the rate ($/kwh)

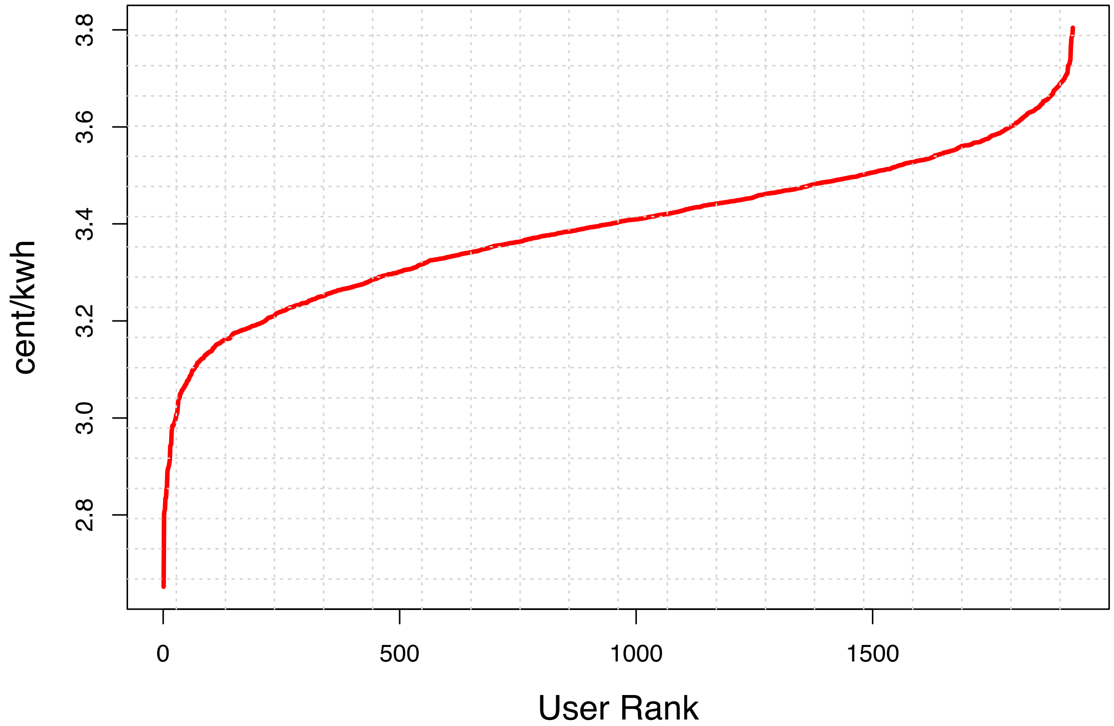
Who forms a group?

How big are the groups?

Group Design

Given a user, it is desirable to

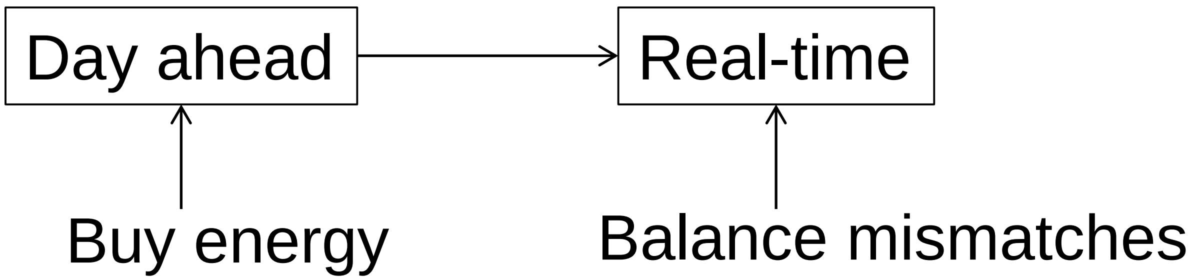
- Join a group with other users ranked lower:
  cost share
- Join a group with more users:
  reduce uncertainty



How do we relate uncertainty to cost?

Cost of Uncertainty

- Two-stage market



- More uncertainty ~ more real-time cost

$$\min_{energy\ purchase} \text{day-ahead cost} + \text{Risk}$$

- Risk is increases with uncertainty

Price of Uncertainty

$$\min_{energy\ purchase} \text{day-ahead cost} + \text{Risk}$$

- Many models of risk, active area of research
- For a class of risk models:

$$\text{Risk} = \sigma \cdot \text{const}$$

Standard deviation of forecast error (σ)

risk aversion, network, … (const)

- Risk is a linear function of forecast error

Rate Optimization

- For a group, has rate ($/kwh):

$$\frac{\text{price} \cdot \text{demand}}{\text{total demand}} + \lambda \cdot CV$$

Increases as group size grows

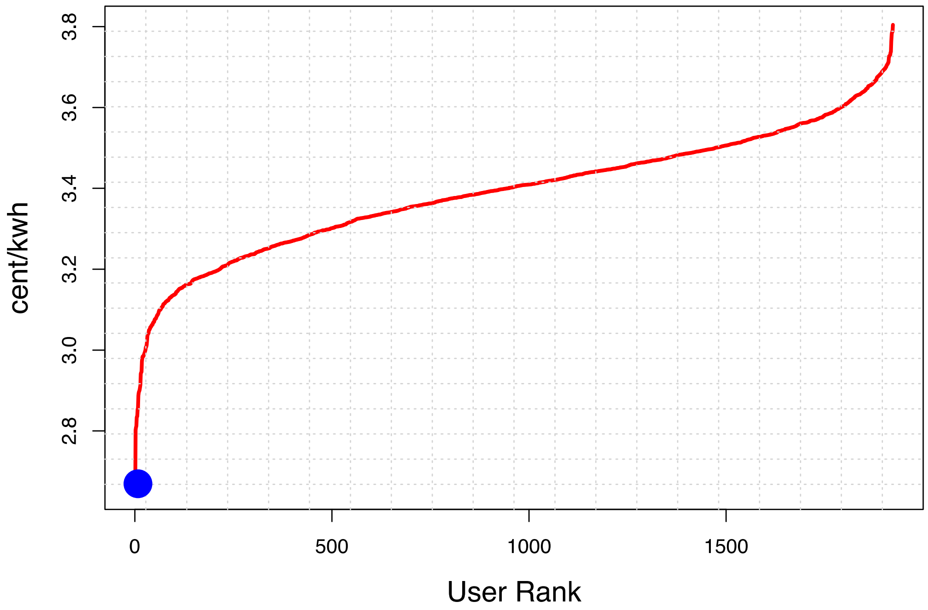
Decrease as group size grows

- Balancing these terms gives the optimal group size and structure

Group Construction Procedure

- Start with the lowest ranked user
- Set a risk level (coefficient of variation level)
- Find enough users to satisfy risk level while minimizing

$$\frac{\text{price} \cdot \text{demand}}{\text{total demand}}$$



(combinatorial, but there is an easy algorithm here)

- Remove this group, and repeat

Stable pricing

- Generate sequence of groups

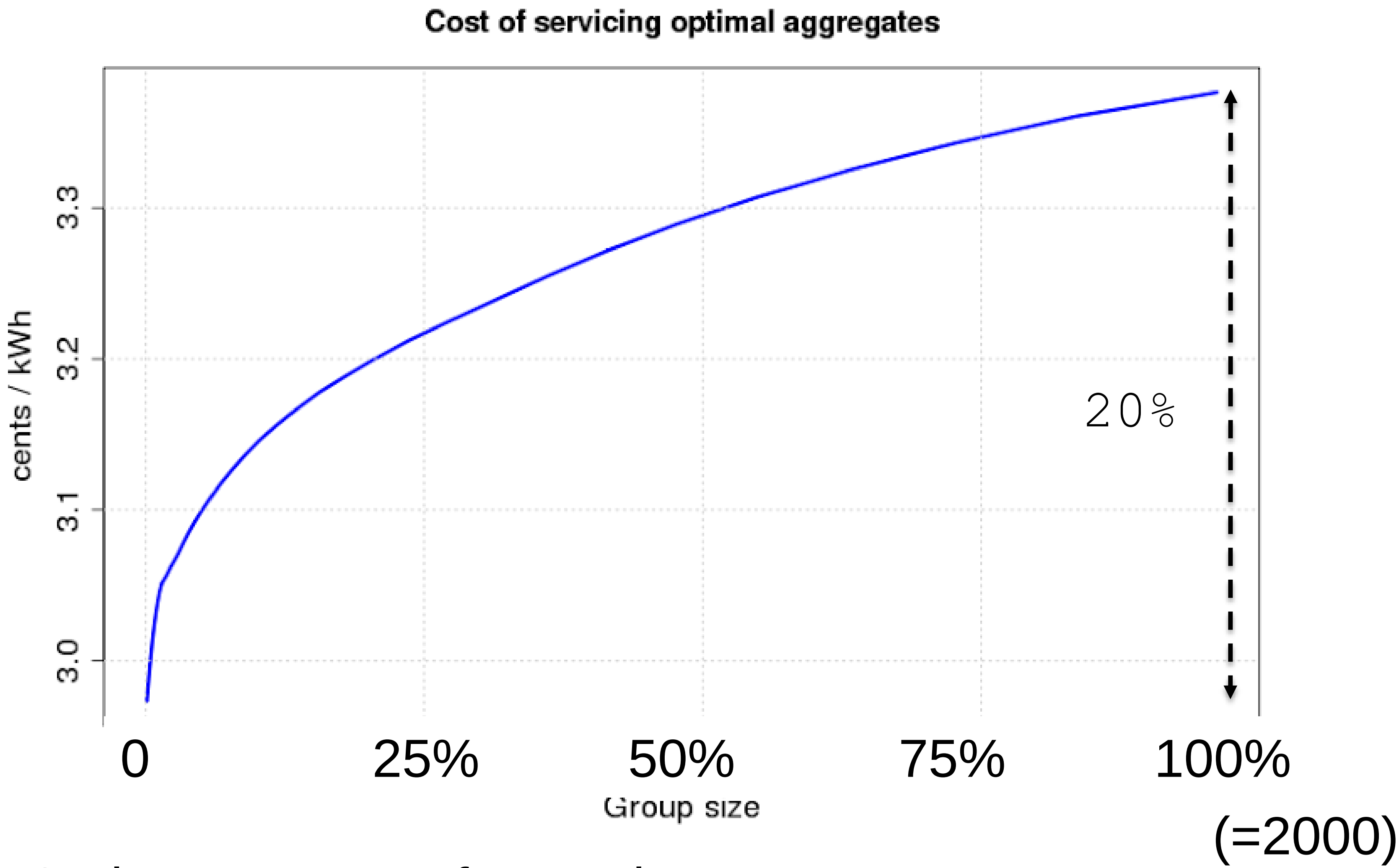
$$S_1, S_2, ..., S_n$$

Such that no member of each group has incentive to defect.

- Users in ERCOT tends to jump from plan to plan frequently, this design is more stable

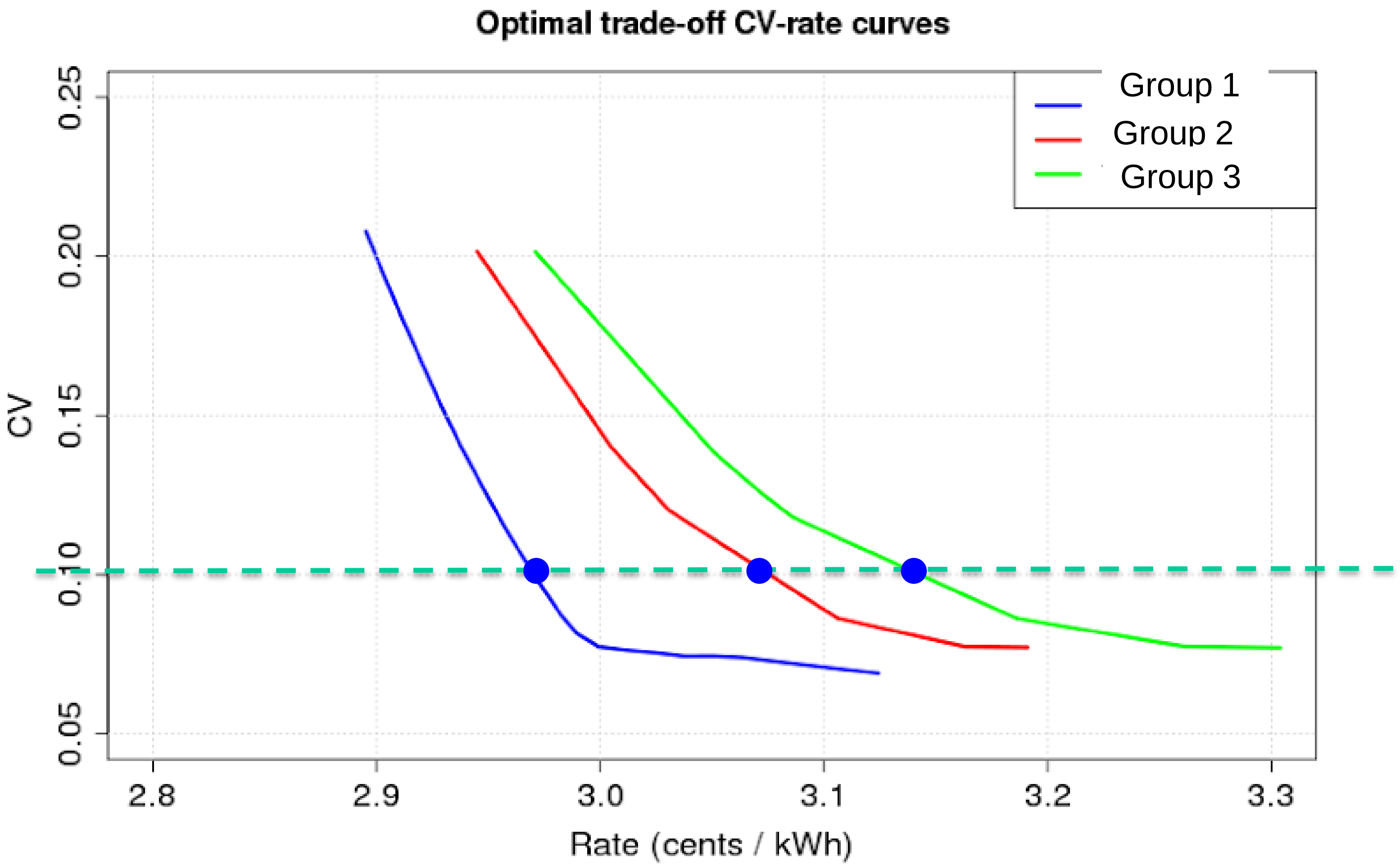
Experiment: learn on data from 100 days, test for rest of the year.

Rates vs. Size of Groups



- Optimum group 1 for varying K.

Group portfolios



- Showing first 3 groups.

Conclusion

- Looking at individual consumptions gives us insight into designing for the aggregate
- Efficient and stable rate design by grouping users
- Many other applications: e.g. demand response