Factored Customer Models for Agent-based Smart Grid Simulation

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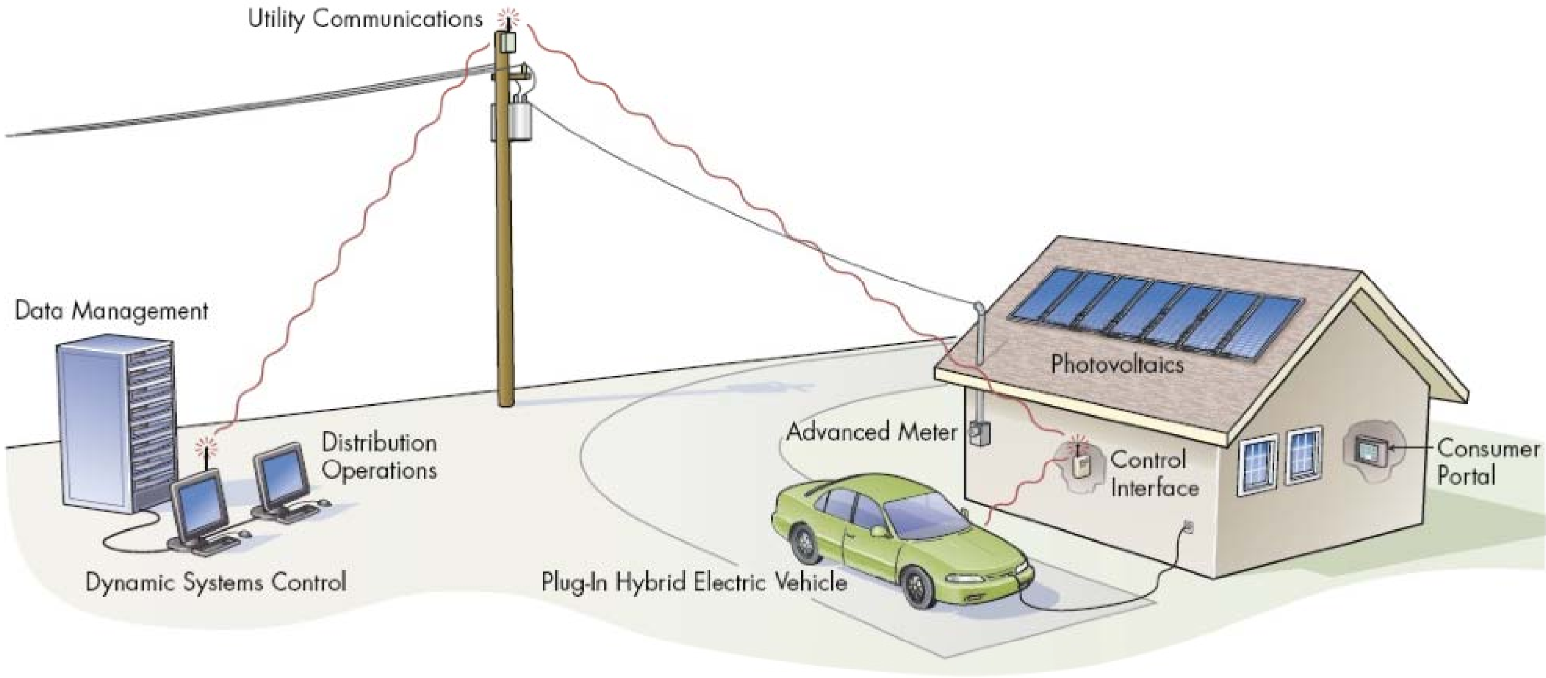
Smart Grid Distribution



Source: EPRI

Distribution Grid Complexity

Source: IEEE

Outline

1. Agent-based Smart Grid simulation
   - Power Trading Agent Competition
2. Intermediary agent strategies
   - Strategy learning for broker agents
   - Interactions of multiple learning broker agents
3. Factored customer models
   - Timeseries simulation using Bayesian learning
   - Decision-theoretic demand side management

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Agent-based Smart Grid Simulation

- Distribution grid modeled as a multi-agent system
  - Focus on emergent economics of self-interested behavior [1]
    - Do not assume rationality nor determinism
  - ✓ Agents contributed by independent research teams
  - ✓ Competitive benchmarking to drive innovation

[1] Leigh Tesfatsion, *ACE: A Constructive Approach to Economic Theory*. Ch. 16, Handbook of Computational Economics, 2005.

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- **Power Trading Agent Competition (Power TAC)**
  - Annual tournament at major AI or MAS conference
    - Builds upon experience with other TAC domains
  - Simulation platform available for offline research
  - Assumes liberalized retail markets
    - Customers have choice of "broker agents"

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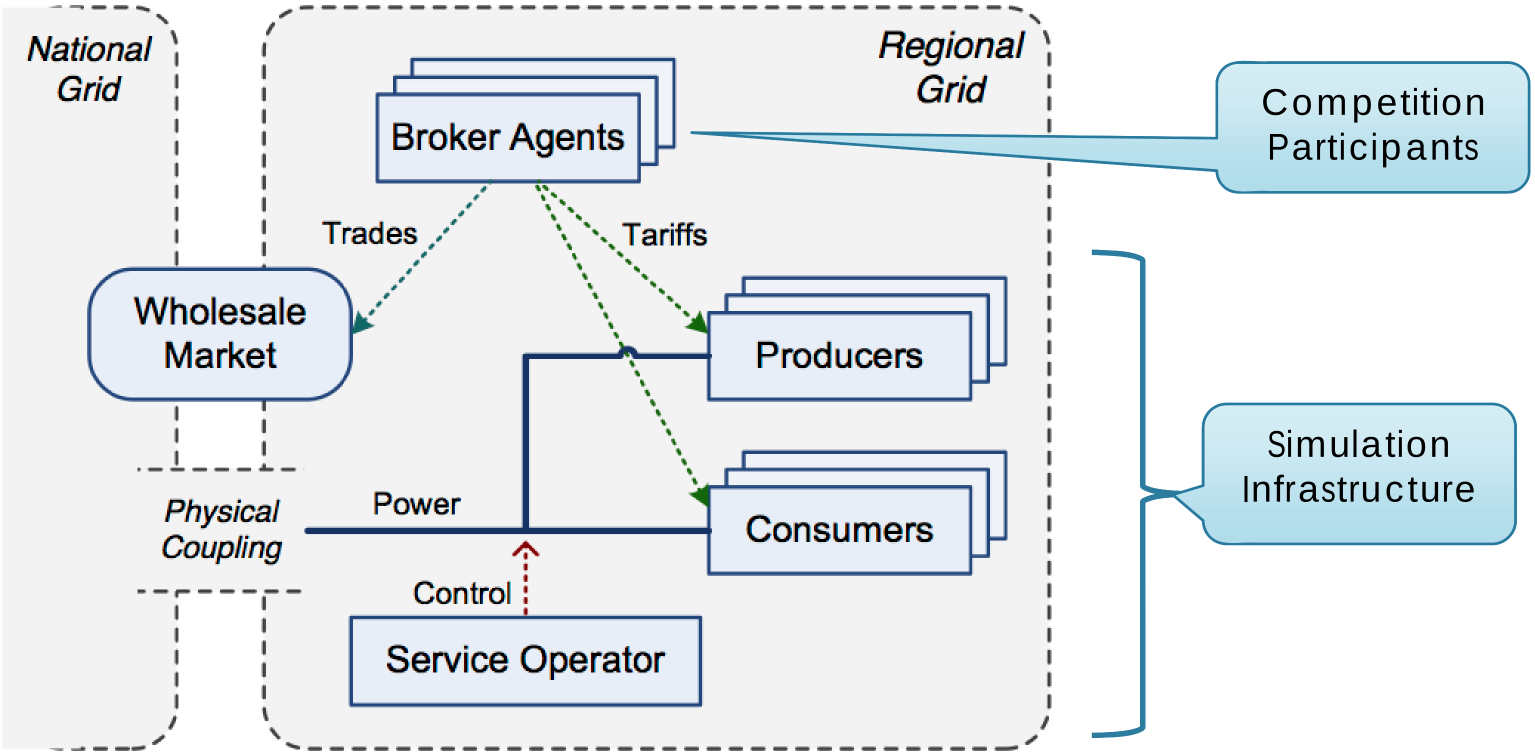
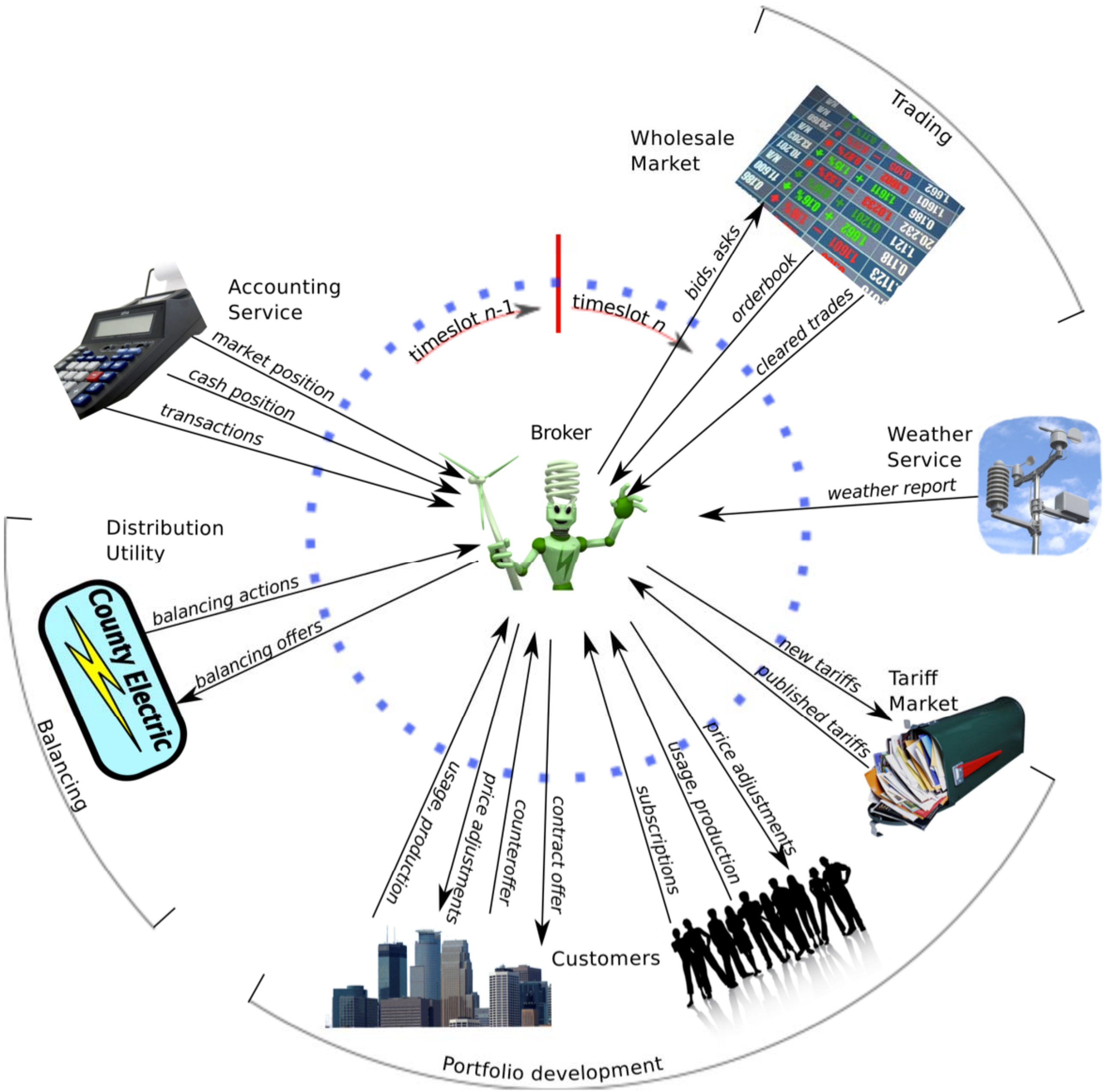
Power TAC Scenario



http://www.powertac.org


Trading
Wholesale
Market
Accounting
Service
timeslot n-1
timeslot n
bids, asks
orderbook
cleared trades
market position
cash position
transactions
Broker
Weather
Service
weather report
Distribution
Utility
County Electric
balancing actions
balancing offers
Balancing
new tariffs
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usage, production
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counteroffer
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Customers
Portfolio development

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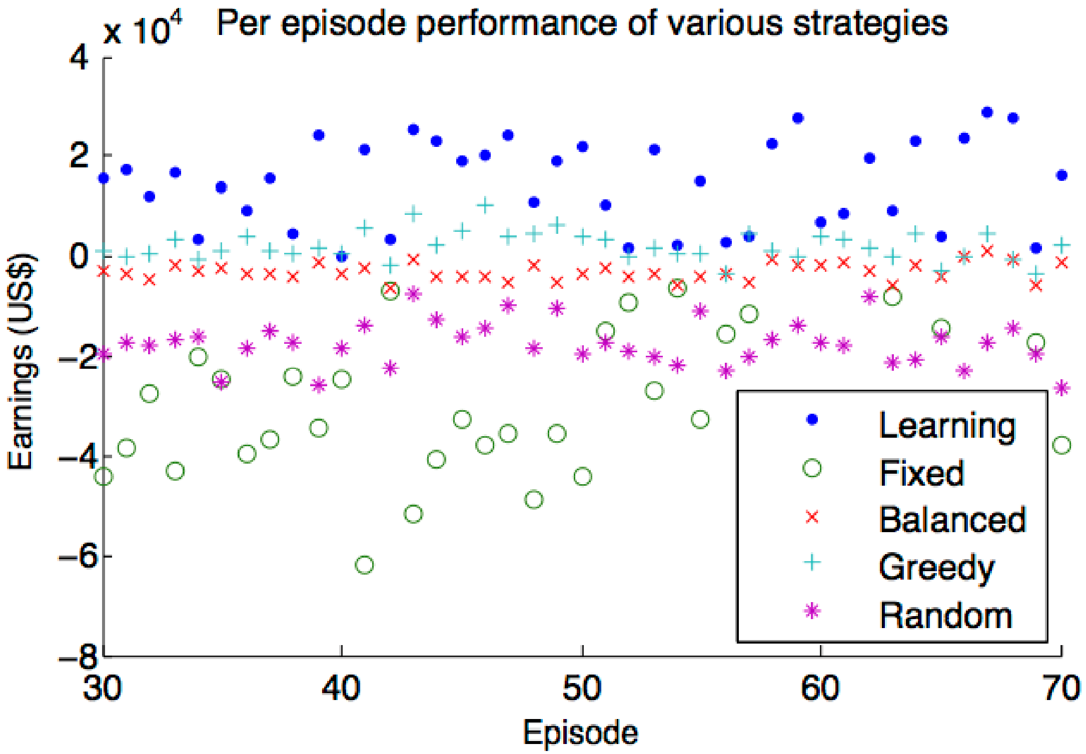
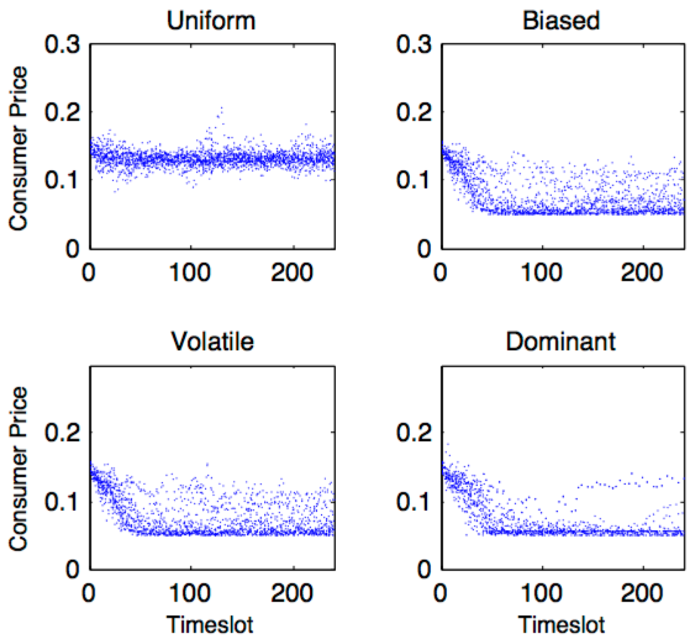
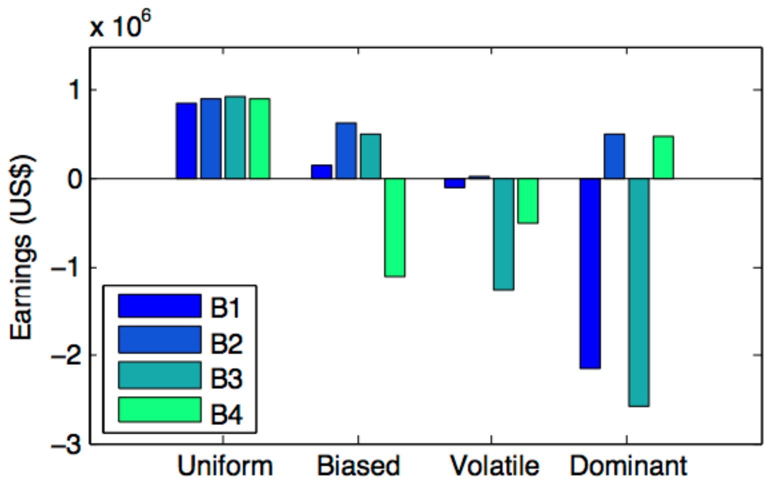
Strategy Learning for Broker Agents



Reddy & Veloso. **Strategy Learning for Autonomous Agents in Smart Grid Markets**. *Twenty-Second Intl. Joint Conf. on Artificial Intelligence (IJCAI)*, Barcelona, 2011.

Interactions of Multiple Learning Broker Agents





Reddy & Veloso. **Learned Behaviors of Multiple Autonomous Agents in Smart Grid Markets**. *Twenty-Fifth AAAI Conf. on Artificial Intelligence*, San Francisco, 2011.

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Factored Customer Models

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  - Trade-off on behavioral accuracy vs. scalability

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- Goals for statistical models:

1. **Representation**
   a. Represent diverse types of consumers and producers
   b. Represent varying levels of granularity
2. **Automated learning**
   - Learn parameters from “real-world” data
3. **Facilitate agent algorithms**
   - Develop algorithms that can be applied in real-world

Factored Customer Model Representation

$$C = \langle \{B_i\}_{i=1}^{N}, \{S_i\}_{i=1}^{N}, U \rangle, \; B_i = \{O_{ij}\}_{j=1}^{M_i}$$

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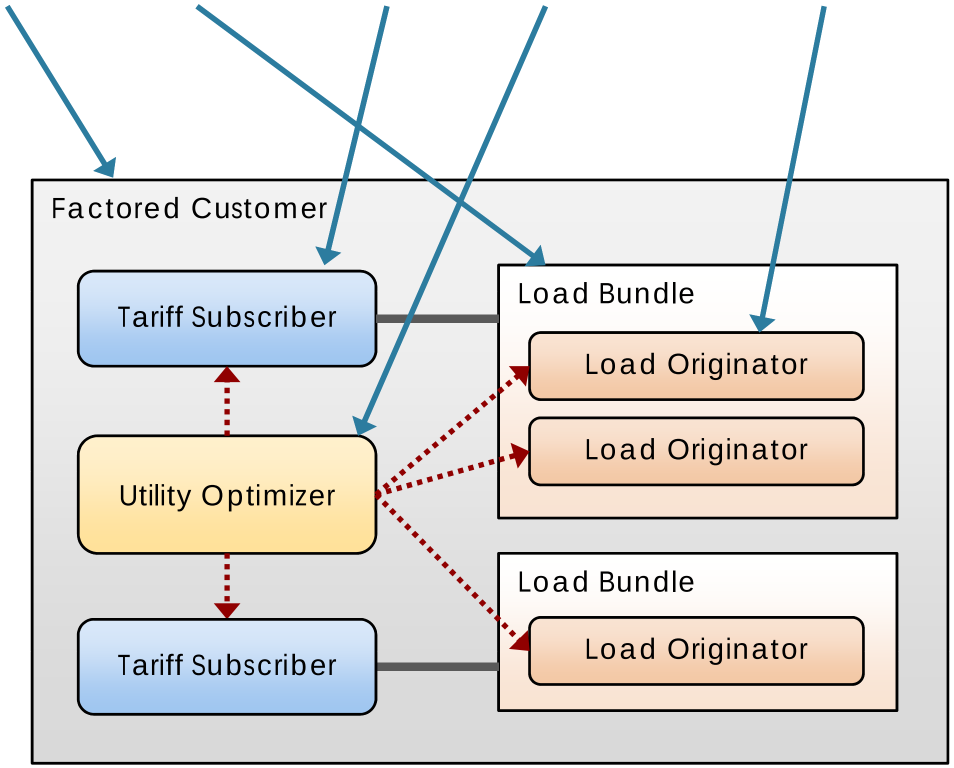

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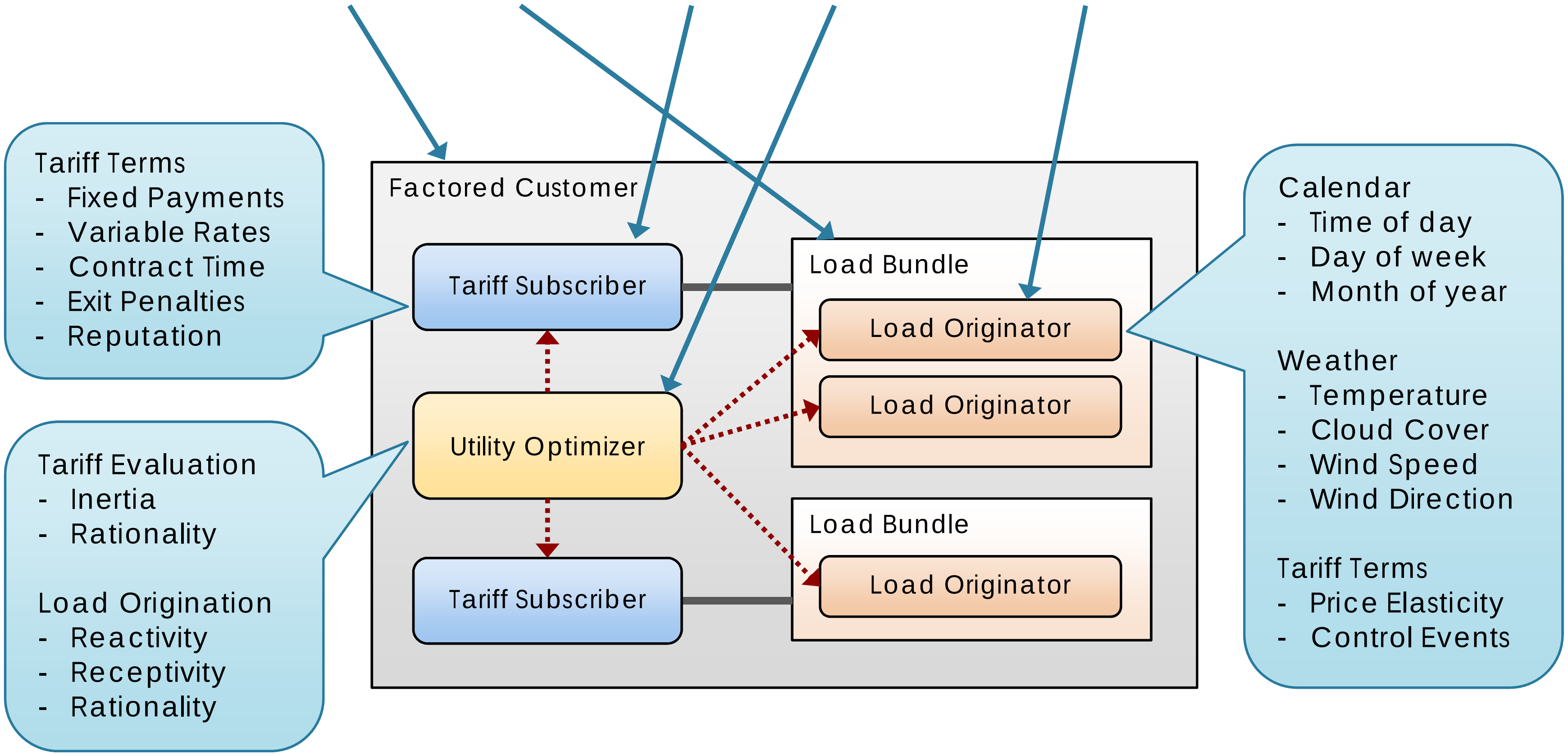

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Timeseries Simulation using Bayesian Learning

- Given small samples of observed data, fit a model that can generate a long range time series forecast
  - Use “similar” samples to improve the fit

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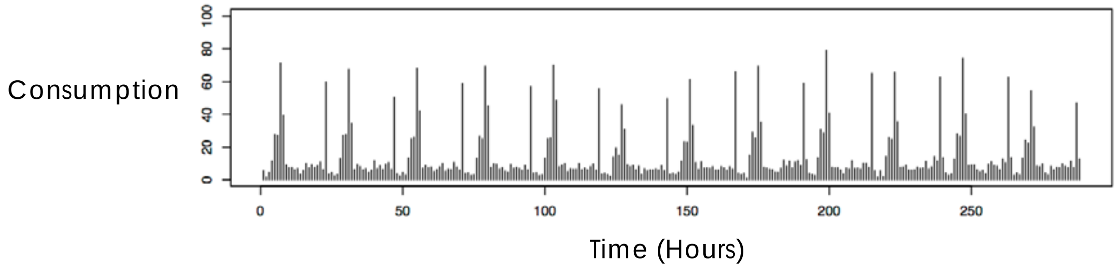
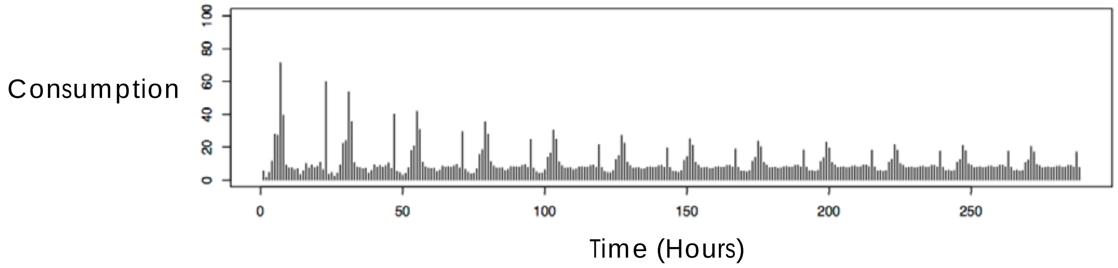
- ARIMA forecasting over **long range** is poor





Bayesian Timeseries Simulation Method

Use *similar* training data

$$Y_{1,t} \sim N(Y_0 + Y_{d,t} + AR_t + MA_t, \sigma^2)$$

$$Y_{2,t} \sim N(Y_0 + Y_{h,t} + AR_t + MA_t, \sigma^2)$$

$$AR_t \leftarrow \phi_1 Y_{t-1} + \Phi_1 Y_{t-24}$$

$$MA_t \leftarrow \theta_1 \varepsilon_{t-1} + \Theta_1 \varepsilon_{t-24} + \theta_1 \Theta_1 \varepsilon_{t-25}$$

$$Y_d \sim N(0, \eta_1^2);\ d = 1..7$$

$$Y_h \sim N(0, \eta_2^2);\ h = 1..24$$

Fit hierarchical Bayesian model using Gibbs sampling

$$Y_t^f \leftarrow Y_0 + Y_{d,t} + Y_{h,t} + AR_t + MA_t$$

$$Y_t^{bf} \leftarrow Y_t^f + \lambda\nu((1-\gamma)Y_{d,t} + \gamma Y_{h,t})$$

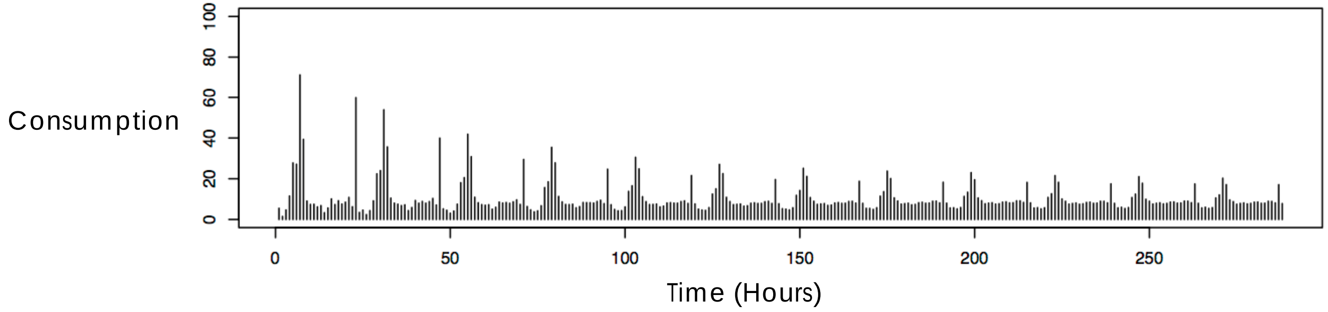
$$\lambda^*, \gamma^* \leftarrow \operatorname*{argmin}_{\lambda,\gamma} \sum_t (Y_t^{bf} - Y_t)^2$$

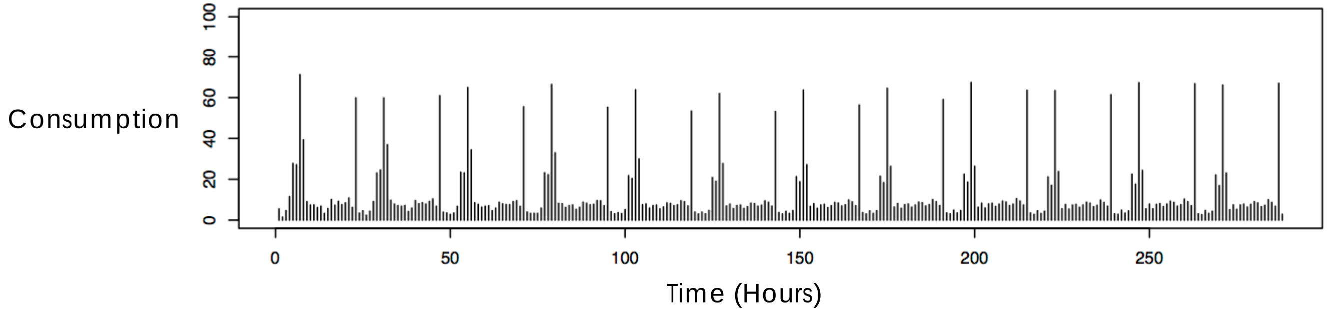
Latent factor optimization to boost fit

$$Z_t^{bf} \sim N(Z_t^f + \lambda^*\nu((1-\gamma^*)Y_{d,t} + \gamma^* Y_{h,t}), \sigma^2)$$

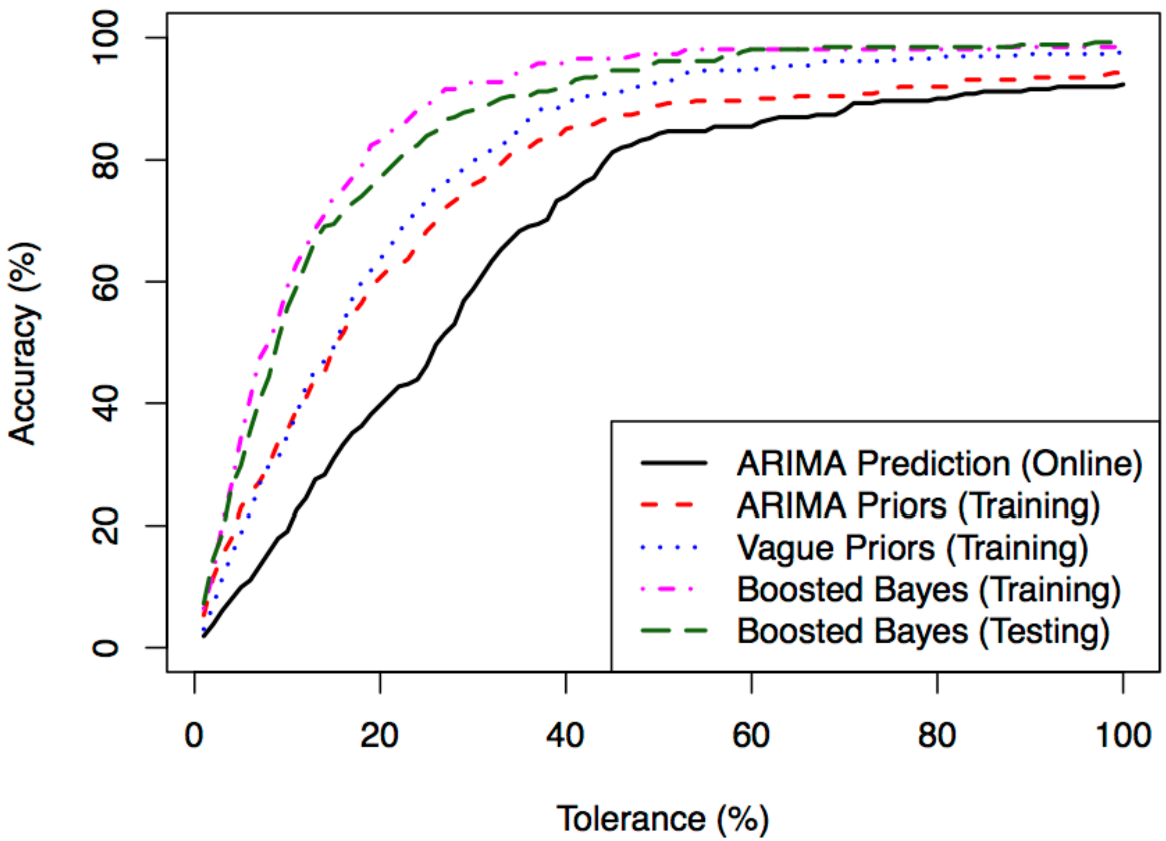
Forecast from small sample

Boosted Bayesian Timeseries Simulation





Boosted Bayesian Forecasting Accuracy



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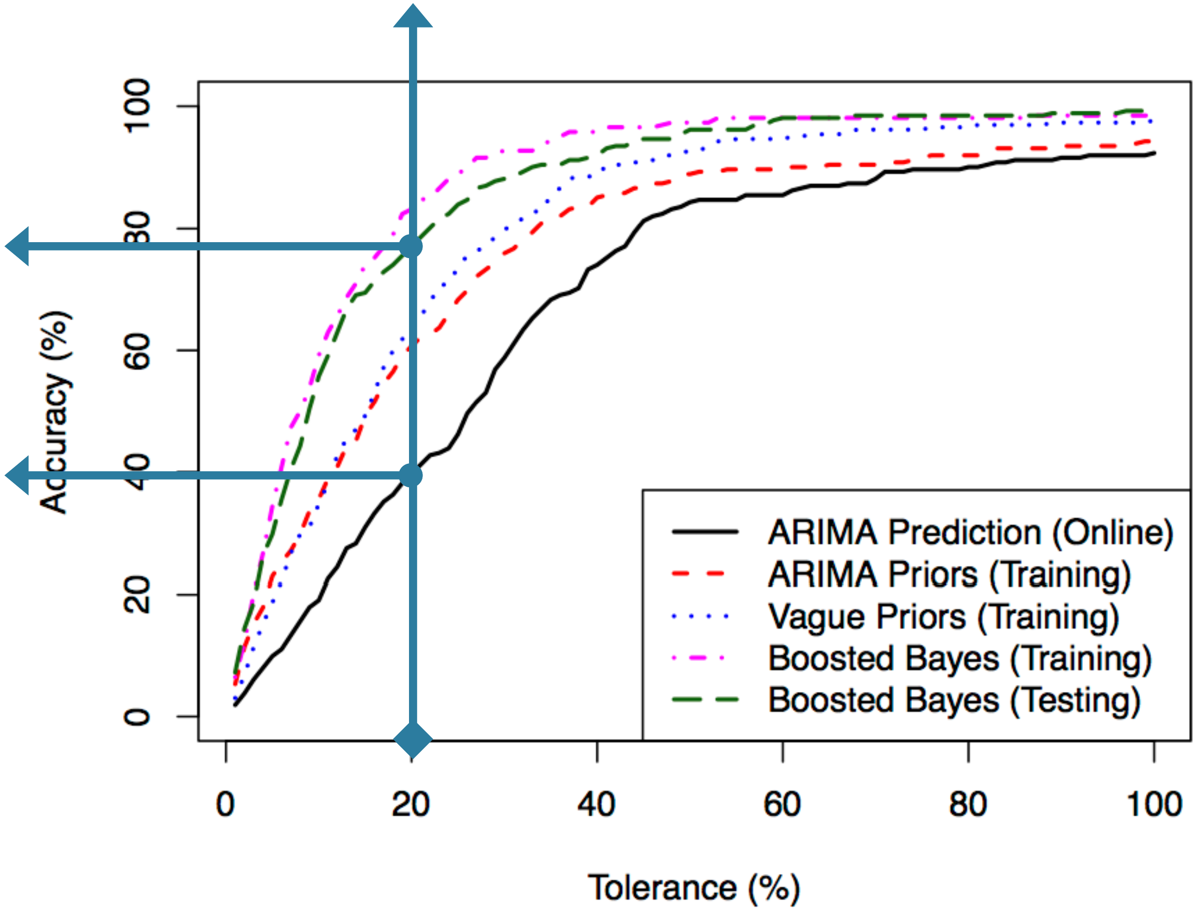

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Decision-theoretic DSM

- Multi-scale decision-making in two dimensions
  1. **Temporal**: Metering period vs. tariff contract period
  2. **Contextual**: Individual load vs. bundle/customer/co-op

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$$\operatorname*{argmax}_{y_t} U^S(p_t, y_t, U^N(y_t))$$

$$\operatorname*{argmax}_{z \in Z_{t'}} U^S_{\square}(P^z_{t'}, Y_{t'}, U^N_{\square}(Y_{t'}))$$

Self Utility

Price Profile

Load Profile

Neighborhood Utility

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- Probabilistic multi-attribute utility model:

$$U^S(\tilde{\rho}_H) = \Delta f_p(\tilde{\rho}_H) + w_D\, D(\tilde{\rho}_H, \hat{\rho}_H) + w_N\, U^N(\tilde{\rho}_H)$$

$$D(\rho_H, \tilde{\rho}_H) = \sum_{t=1:H} (\rho_t - \tilde{\rho}_t)^2 \qquad Pr(z) = \frac{e^{\lambda U^S_{\boxtimes}(z)}}{\sum_Z e^{\lambda U^S_{\boxtimes}(z)}}$$

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Monte Carlo Sampling

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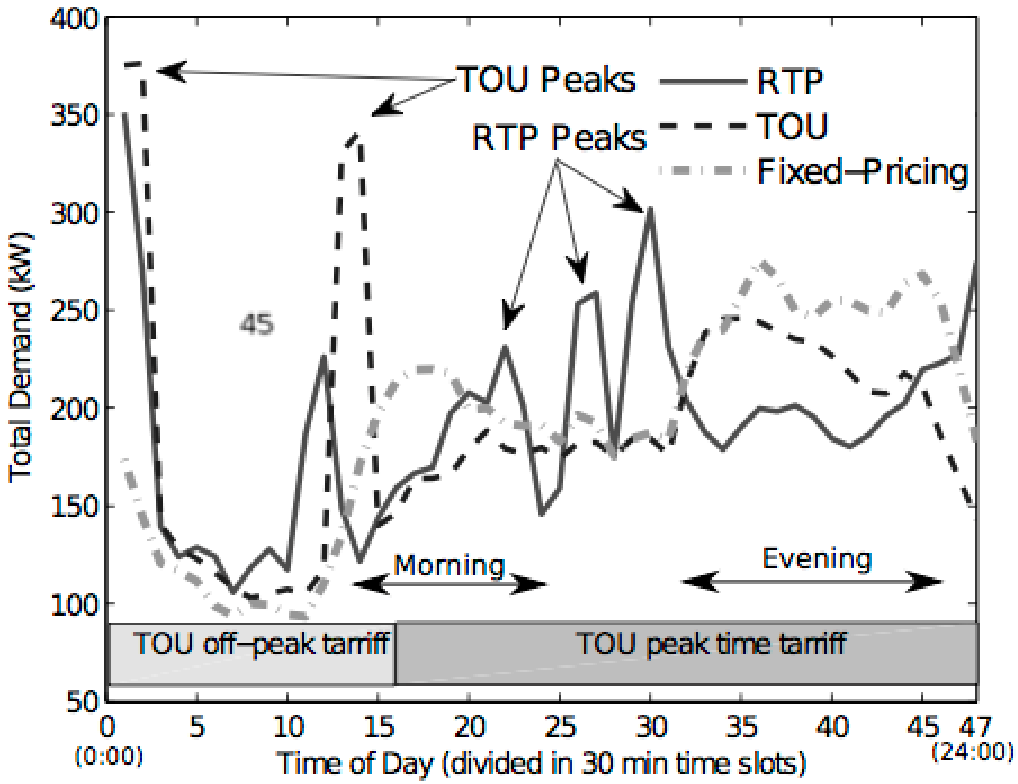
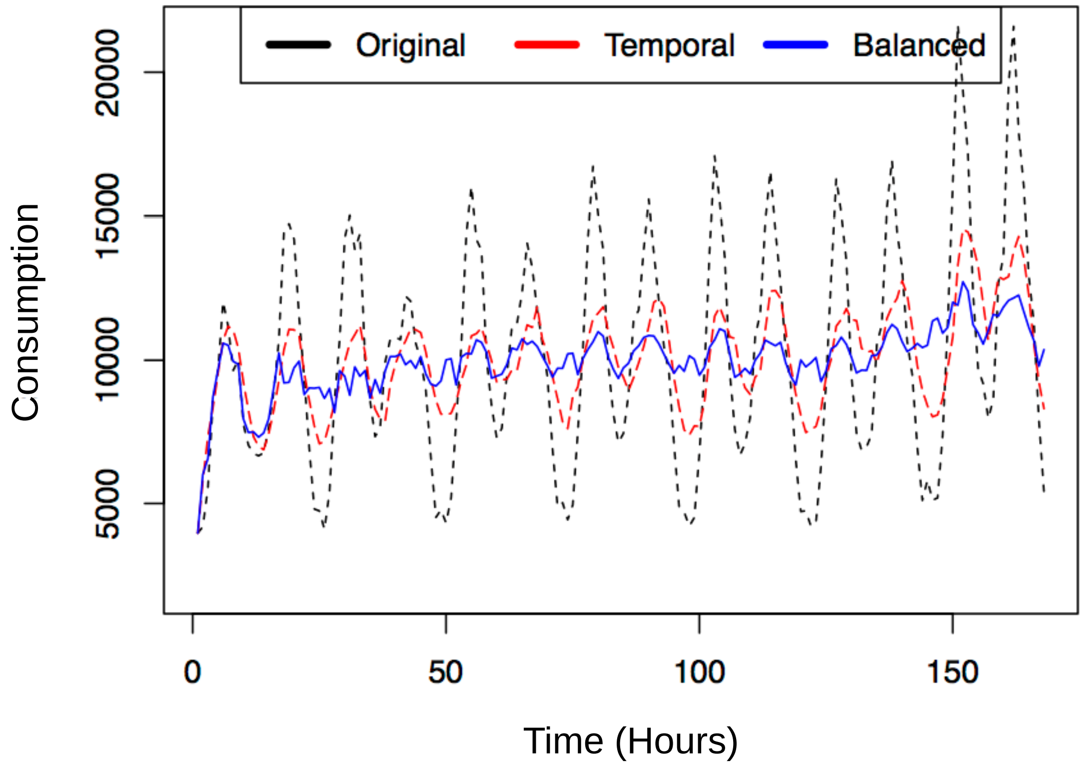
Peak Shifting (Herding) Behavior



Ramchurn, et al. *Agent-Based Control for Decentralised Demand Side Management in the Smart Grid*. Autonomous Agent and Multi-Agent Systems (AAMAS), 2011.

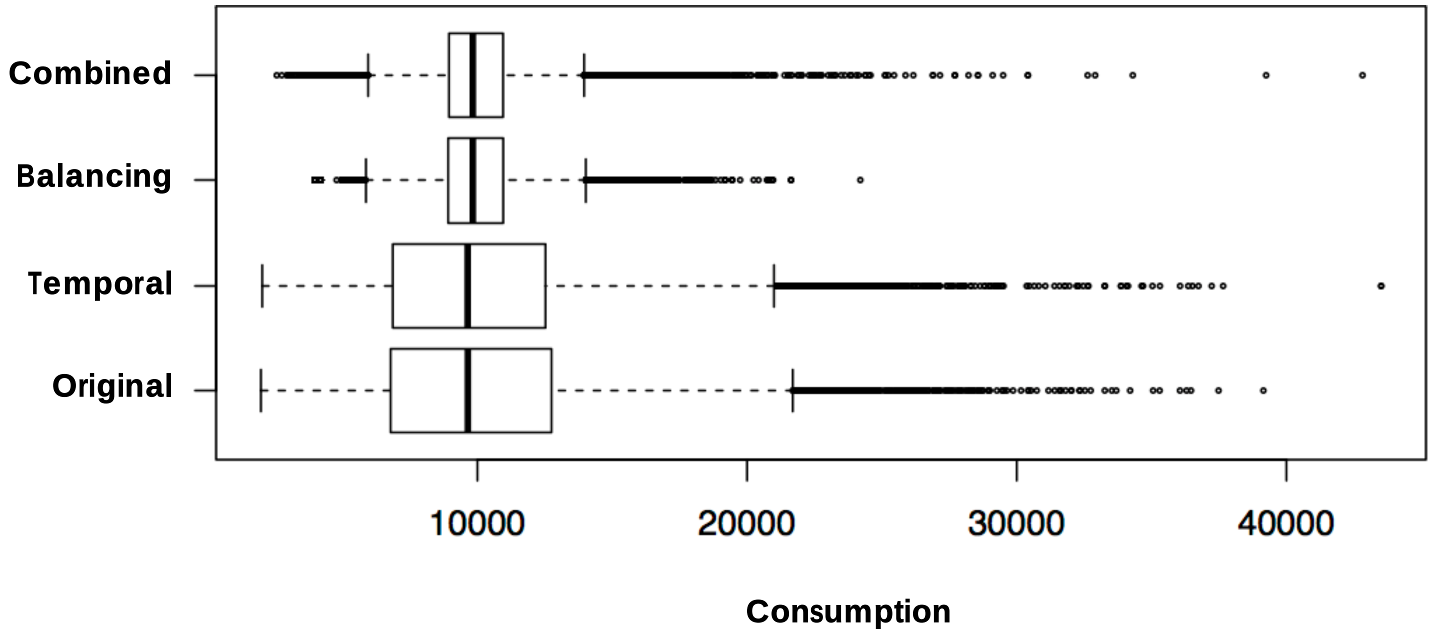
Household Demand Shifting

- Based on data from Germany's *MeRegio* project

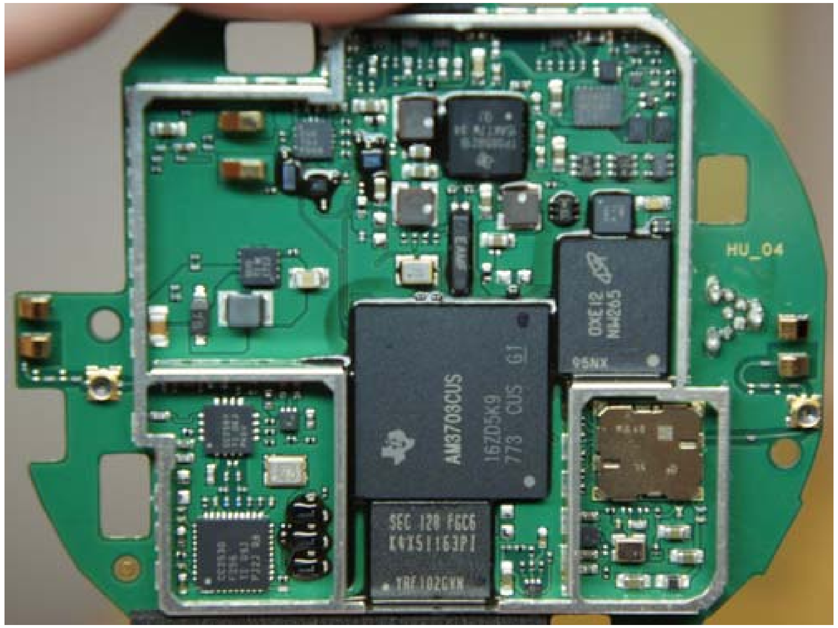


Household Demand Shifting

- Lower variance and cost savings of **~10%**



DSM Deployment Options



ARM Cortex-A8 and Zigbee SoC

Conclusion

- Summary
  - Versatile customer model representation
  - Decision-theoretic algorithms for DSM
  - Bayesian learning algorithms for timeseries simulation

- Future Work
  - Customer type-specific factor modeling
  - Non-cooperative decision-making models

- Participating in Power TAC
  - Hosted at AAMAS, Valencia, June 2012
  - More information at http://www.powertac.org

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