Multiagent Coordination for Electricity Demand Management in Consumer Cooperatives

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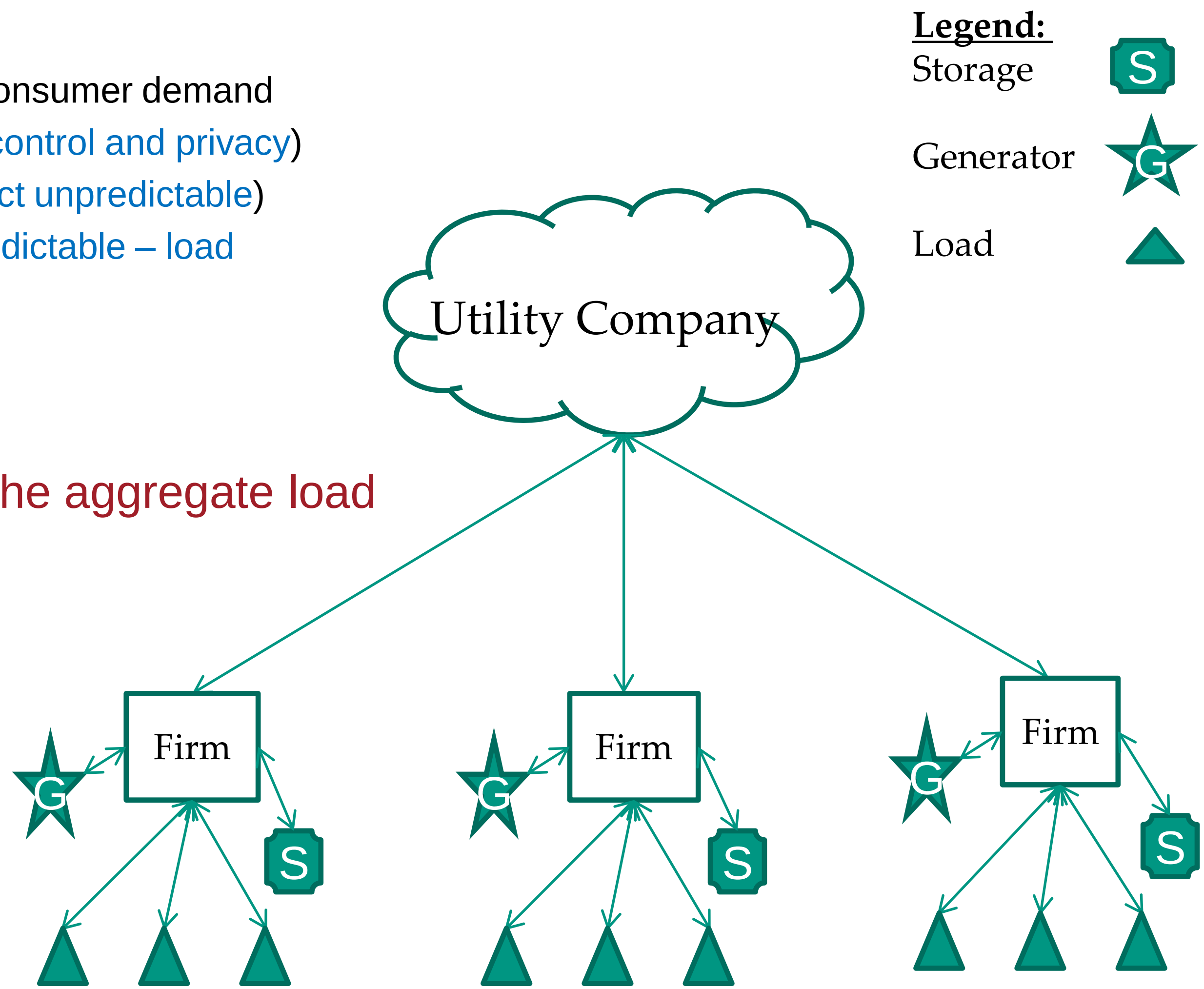
Motivation for Demand Side Management

- Reducing peak electricity demand is a key problem in creating energy efficient societies
- Increase of renewable energy sources increases supply variability

Current Attempts at Demand Side Management

Methods used for controlling consumer demand

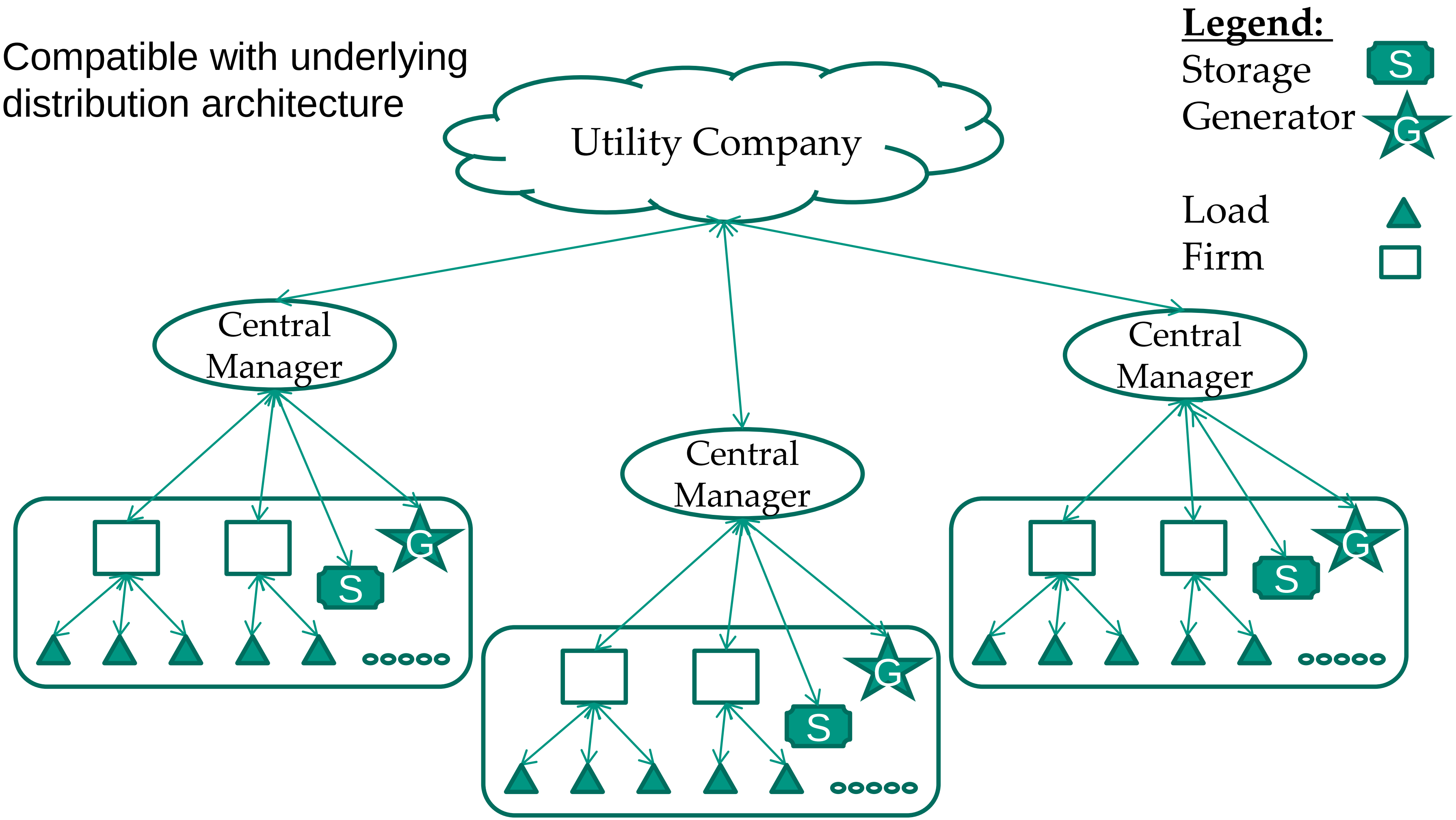
- Direct Load Control (no control and privacy)
- Time-of-use Pricing (effect unpredictable)
- Real Time Pricing (unpredictable – load synchronization)



➢ Focus on controlling the aggregate load

Organization with Central Manager

Compatible with underlying distribution architecture



Advantages of Partial Centralization

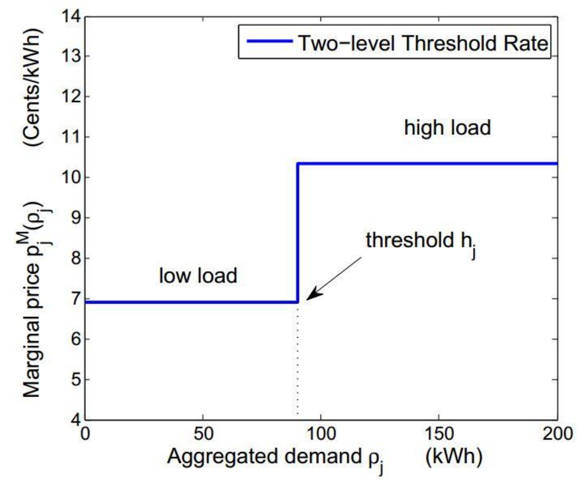
- Individual customers in consumer groups retain control of their own appliances (and some degree of privacy)
- Consumers can obtain electricity at better prices
- From utilities perspective, consumer groups are large enough to have more predictable demand shifts

A. Veit, Y. Xue, R. Zheng, N. Chakraborty, and K. Sycara. Multiagent Coordination for Energy Consumption Scheduling in Consumer Cooperatives. 27th AAAI Conference, Bellevue, WA, July, 2013.

Problem Formulation: Assumptions and Challenges

Assumptions:

- Central Manager (CM) and all firms (agents) know the electricity prices for the whole planning horizon
- Agents' consumption constraints and demand shifting costs are private
- Agents do not communicate their private constraints/costs neither with other agents nor with the CM
- Agents are non-strategic, report their demands truthfully to the CM
- The electricity rates follow a threshold structure



Challenges:

- The CM must optimally coordinate the agents in the face of incomplete information
- Agents must compute their demand without knowledge of others' demands or constraints

Overall Optimization Problem

Electricity cost for each agent: $\sum_{j=1}^{M} \mathrm{p}_j(\rho_j)\, r_{ij} + \mathrm{g}_i(\mathbf{r}_i)$

- $\sum_{j=1}^{M}$: sum over all time slots
- $\mathrm{p}_j(\rho_j)$: price function in time slot j of aggregated demand
- r_{ij}: demand of agent i in time slot j
- $\mathrm{g}_i(\mathbf{r}_i)$: individual cost function of agent i

$$\min \mathrm{C}(\mathbf{R}) := \sum_{i=1}^{N} \sum_{j=1}^{M} \mathrm{p}_j(\rho_j) r_{ij} + \sum_{i=1}^{N} \mathrm{g}_i(\mathbf{r}_i)$$
$$\text{s.t.} \quad \mathbf{r}_i \in \mathcal{X}_i, \; \sum_{j=1}^{M} r_{ij} = \tau_i.$$

- $\sum_{i=1}^{N}$: sum over all agents
- $\mathbf{r}_i \in \mathcal{X}_i, \; \sum_{j=1}^{M} r_{ij} = \tau_i$: demand constraints of agents

➢ **Overall problem is a convex optimization problem**

Individual Agent Problem

Central Problem

$$\min \mathrm{C}(\mathbf{R}) := \sum_{i=1}^{N} \sum_{j=1}^{M} \mathrm{p}_j(\rho_j) r_{ij} + \sum_{i=1}^{N} \mathrm{g}_i(\mathbf{r}_i)$$
$$\text{s.t. } \mathbf{r}_i \in \mathcal{X}_i,\ \sum_{j=1}^{M} r_{ij} = \tau_i .$$

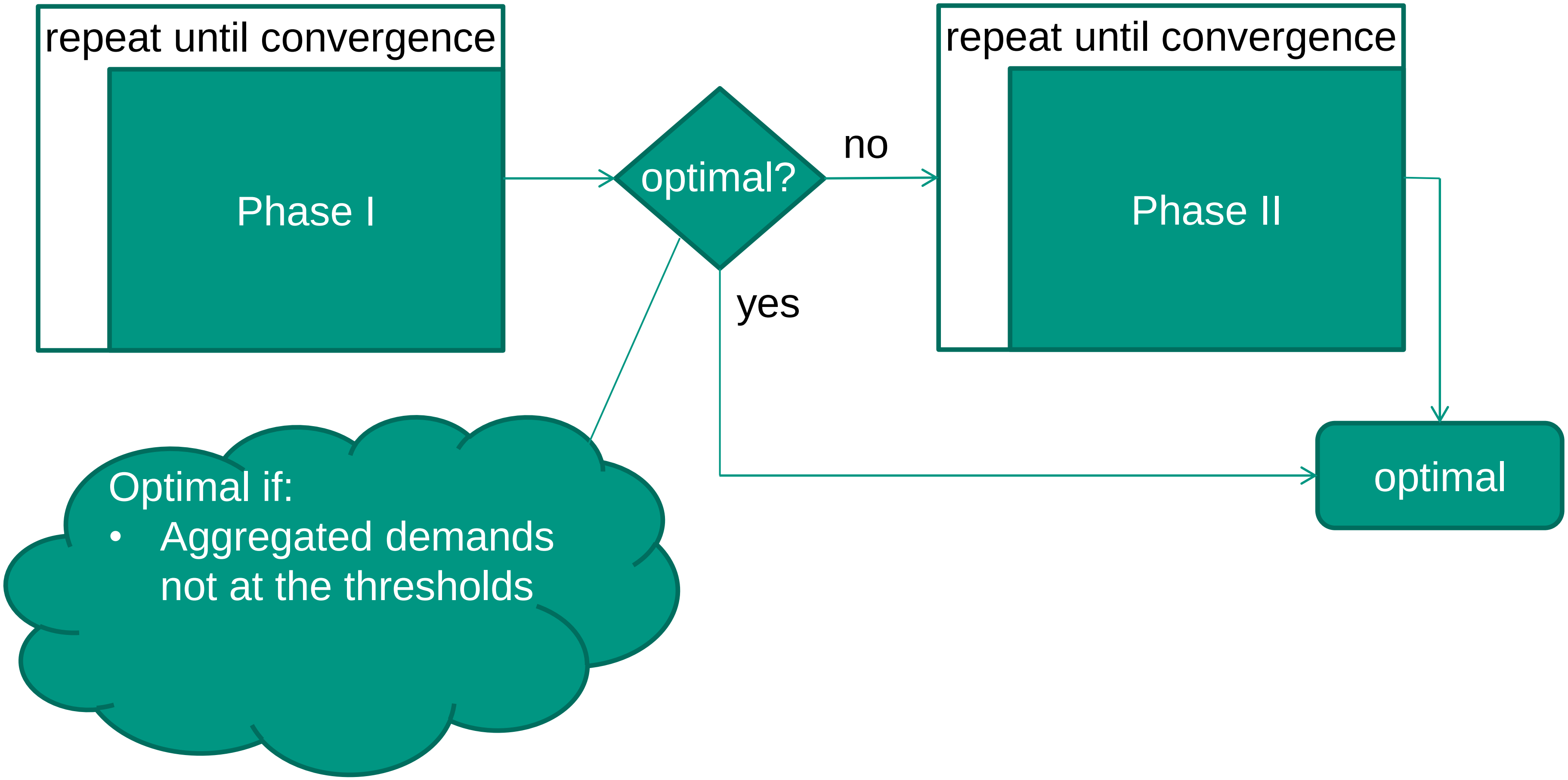
- Constraints are agent specific → naturally separable
- Objective function is coupled, because the price depends on the aggregated consumption of all agents

➢ Primal decomposition, considering the virtual price signal $\mathrm{s}_{ij}^{v}(r_{ij}|\mathbf{R})$

Agent Problem

$$\min \mathrm{C}_i^{v}(\mathbf{r}_i|\mathbf{R}) := \min \sum_{j=1}^{M} \mathrm{s}_{ij}^{v}(r_{ij}|\mathbf{R})\, r_{ij} + \mathrm{g}_i(\mathbf{r}_i)$$
$$\text{s.t. } \mathbf{r}_i \in \mathcal{X}_i,\ \sum_{j=1}^{M} r_{ij} = \tau_i .$$

Iterative Coordination Algorithm



Algorithm: Phase I

1. *Initialization*: All agents compute an initial demand profile

2. *Virtual price signal*: CM computes virtual price signals based on

   the aggregated and individual demand in each time slot. The virtual price signal gives each agent a decision rule of computing price as a function of demand for each time slot

$$s_{ij}^{M}\left(r_{ij}\right)=\begin{cases} p_j^H & r_{ij}>h_{ij} \\ p_j^L & r_{ij}\leq h_{ij} \end{cases}$$

3. *Agent Problem*: Agents compute
   their best demand profile according to their virtual price signal
3. *Termination Criterion*: CM computes
   - If no agent changed its demand profile,
     - and if no aggregated demand is at any threshold, algorithm stops (solution is optimal).
     - Otherwise, CM goes to Phase II
   - Otherwise CM goes back to step 2.

Algorithm: Phase II

1. *Initialization:* Based on the last iteration of Phase I.
2. *Virtual price signal :* CM computes price signals for each agent based on the aggregated and individual demand in each time slot and the marginal demand valuations of the agents for time slots at a threshold. Marginal demand valuation is the change (positive or negative) of agent's cost, for one additional unit of electricity above the threshold.
3. *Agent Problem: Agents compute*
   their best demand profile according to the virtual price signal and marginal demand valuation for time slots at a threshold
4. *Termination Criterion:* If
   - no agent changed its demand profile and
   - no beneficial shift exists between two agents in any time slot at threshold, algorithm stops.
   - Otherwise CM goes back to step 2.

Convergence Results

Lemma 1: The algorithm strictly reduces the total cost in every iteration

Proof: Based on algebraic calculations.

Theorem 1: The iterative algorithm always converges.

Proof: Follows from the following facts:

a) there is a finite lower bound on the total cost,

b) the total cost in each iteration decreases (from Lemma 1).

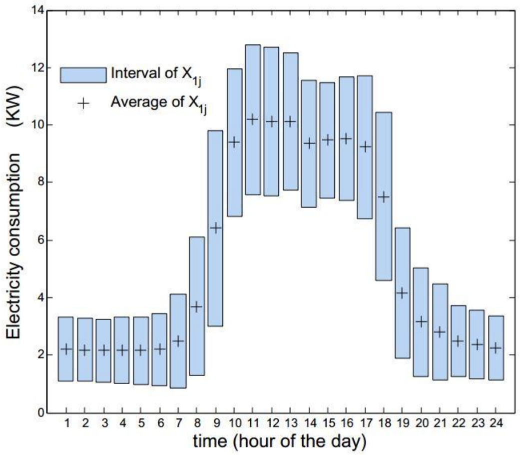
Theorem 2: The converged solution **R** is the optimal solution

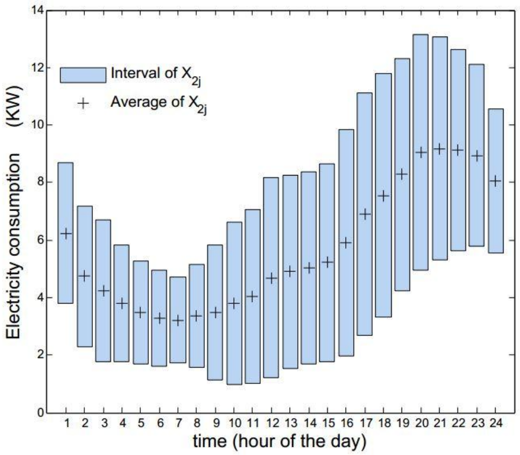
Proof: By contradiction

Parametrization

Agents

- Heterogeneity of Demand Profiles
- Flexibility of shifting demand



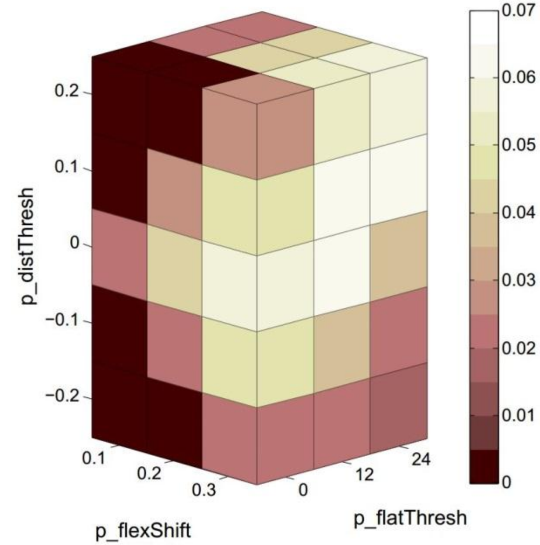


Consumer data: http://www.ucd.ie/issda/data/commissionforenergyregulation/

Price data: http://www.eex.com/en/Market%20Data.

Simulation Results

- As the flexibility of shifting demand increases, the cost reduction increases.
- We varied the percentage of consumers in each of the two classes. The coordinated behavior leads to similar cost reductions (up to 7%) over uncoordinated consumers in each of the consumer classes as well as mixed groups.
- The convergence time scales linearly with the population size.
- 225 scenarios, 4 repetitions of each, for each value of # of agents



Number of agents	Share of potential cost reduction achieved	Average Number of iterations until convergence
20	0.9970	22.09
40	0.9967	26.07
60	0.9963	33.91
80	0.9962	34.44
100	0.9964	40.03

Conclusion

- Presented an algorithm for coordinating electricity demand of consumers organized into consumer groups.
  1. To flatten peak demand by reducing overall electricity consumption cost.
  2. To maintain privacy of individual consumers.
- Proved convergence of the algorithm to the optimal solution.
- Performed simulations of the algorithm to evaluate
  1. the effects of the cooperative's parameters on the cost reduction.
  2. convergence properties of the algorithm.

Future Work

- Consider a problem formulation where there is a centralized generation facility and a storage facility (initial optimization results obtained).
- Consider a problem formulation, where the planning horizon is longer than the horizon for which the price is known, because then the cooperative faces uncertainty in electricity prices.
- Investigate whether an approximation guarantee for the central solution is possible, if agents cannot solve their individual problems optimally.
- Study the coordinator as market maker.