Contributions
- Develop model of electricity markets that accounts for many of the complexities in demand and production
- Complexities prevent use of standard cost-sharing techniques
- We develop cost-sharing schemes that address stability, envy-freeness, transparency, budget balance, and scalability

Motivation
- Make demand more responsive to grid conditions
- Make it cheaper to integrate renewable sources, which generate a varying amount of power, into the grid
- Consumers willing to change their behavior if they are sufficiently compensated and if it is not too annoying
- Problem: consumers respond slowly to incentives
- Approach: each consumer is represented by an autonomous agent, who knows their preferences
- We focus on the problem of coordinating agents and determining “fair” payments that incentivize consumers to coordinate

Model
- Each agent $i$ has electricity use profiles $\Pi_i$
- Each profile $\pi \in \Pi_i \subset \mathbb{R}^T$ represents an acceptable consumption pattern (electricity use per period in kWh)
- Each profile has a value $V_i(\pi)$ in dollars
- Matching $\mu$ maps consumer $i$ to a producer $\mu(i)$ and a profile $\mu(\pi)
- Each producer $j$ has a price function $P_j : \mathbb{R}^T \rightarrow \mathbb{R}$ representing what they would charge for serving a particular demand profile
- Limited ramp rate
- Shutdown costs: if demand < minimum economic generation level (MEGL), an additional fee is charged
- Base layer: inexpensive, slow to adjust
- Tracking layer: expensive, quickly adjustable
- Social welfare: sum of profile values minus sum of producer prices

Approach to Cost Sharing
- View as a cooperative game
- Coalitions consist of a producer and consumer agents, value is social welfare
- Negative results: core and Nash-stable allocations may not exist

Desiderata
- Stability and budget balance
- Envy-free: no agent would prefer the matching of an identical agent
- Transparent: it should be clear why an agent is paying what they pay
- Computationally scalable: tractable for large numbers of agents

Shapley-Like Payments
- We can apply Shapley values. The Shapley value of consumer $n_i$ matched to producer $m_j$ under $\mu$ is:
  \[ s(n_i) = \alpha \sum_{S \in \mu^{-1}(\{n_i\}) \setminus \{n_i\}} P_{m_j}(\text{dem}_{\mu}(S \cup \{n_i\})) - P_{m_j}(\text{dem}_{\mu}(S)) \]
- $\alpha$ is a normalizing constant, $\text{dem}_{\mu}(x)$ is the demand of the agents in set $x$ under matching $\mu$
- Intuition: Shapley payment for $n_i$ is the average marginal cost over all orders that $n_i$ could be assigned to producer $m_j$
- We allow payments to be adjusted $\pm 10\%$ to increase stability

Similarity-Based Envy-Free Payments
- Envy-freeness is very weak in this context because usually no two agents will want to use the same profile
- Similarity-based envy-freeness (SBEF) generalizes envy-freeness: demand profiles that are “close” should have a similar price
- Partition demand profiles, fix unit price in each partition, and optimize prices for stability
- Intuition: SBEF payments are fair because consumers with profiles in different clusters pay similar prices to be similar across partitions

Experiments
- 50 consumers, 2 producers, 4 profiles per consumer, 50 trials
- Model of residential energy use in San Antonio, Texas, July

Shapley-Like Payments
- Do a local search to improve stability while sacrificing a small amount of social welfare ($< 2\%$)
- Payments have max defection incentive of $\leq 7.5$ on avg.
- Computationally expensive
- Well-understood

SBF Payments
- Very stable: max defection incentive is less than $2$
- Computationally efficient: we can solve instances with 2500 in 30 minutes
- Stability $\uparrow$, envy-freeness $\downarrow$ as number of partitions $\uparrow$

Future Work
- Elicitation of demand profiles
- Make use of historical data
- Use envy-freeness partitions to compute optimization