Cyber physical social systems: Modelling of consumer assets and behavior in an integrated energy system

in

Energy Systems Integration 102 – Research Challenges

by

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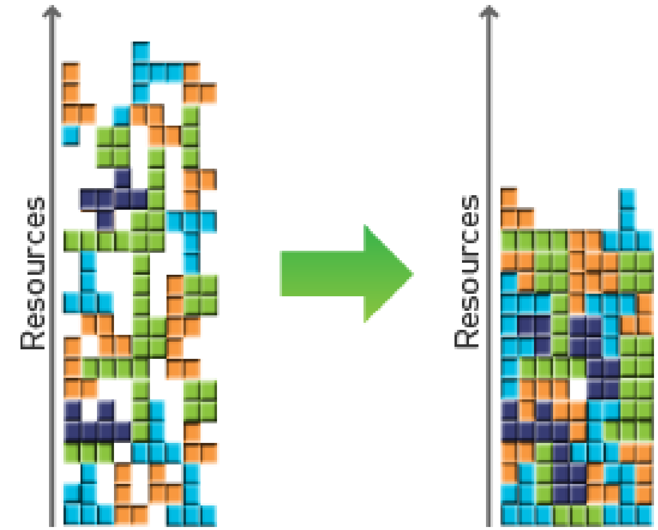
Outline

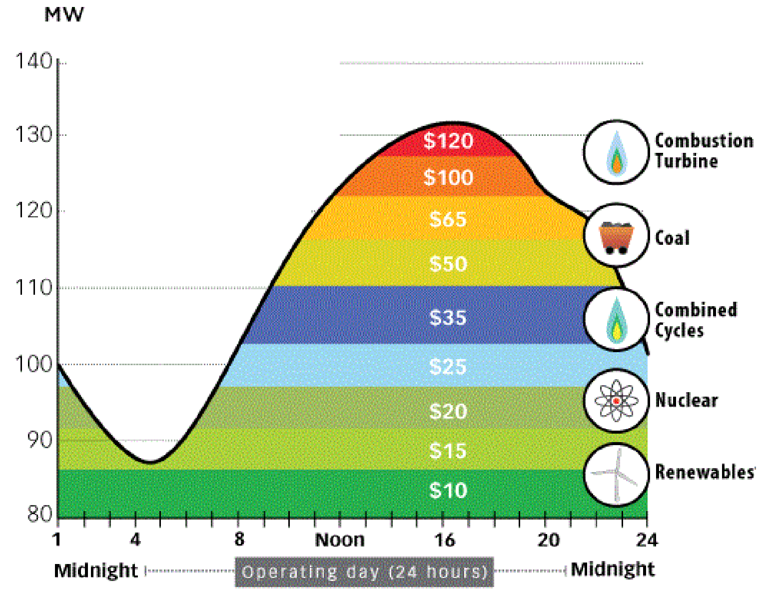
- introduction to resource allocation
- resource allocation in Smart Grid
- role of customers in resource allocation
- a method for incentivizing customers
    - customer incentive pricing
    - modeling the customer assets and behavior
- conclusions and future directions

Introduction to Resource Allocation

- **what is resource allocation?**
  - assignment of limited resources to perform useful work
- *optimal* resource allocation problems, in general, are NP-Complete

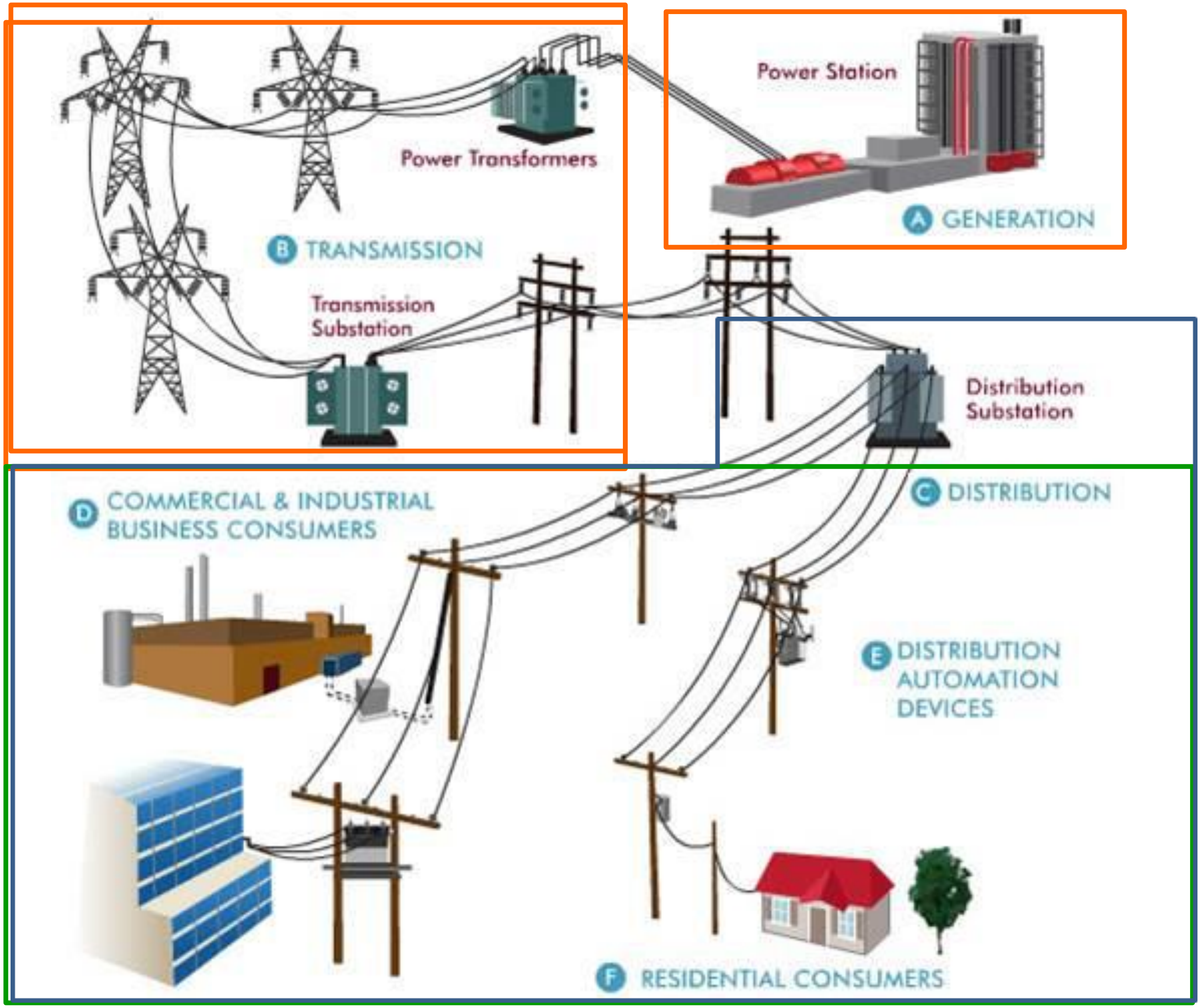


- in high-performance computing (HPC):
  - allocate HPC resources to parallel applications
- in electric power systems:
  - allocate generation resources to energy consumers



- Figure sources
  - [1] Global Nettech. [Online] http://goo.gl/XjGx18
  - [2] PJM Learning. [Online] http://goo.gl/vvvNyj

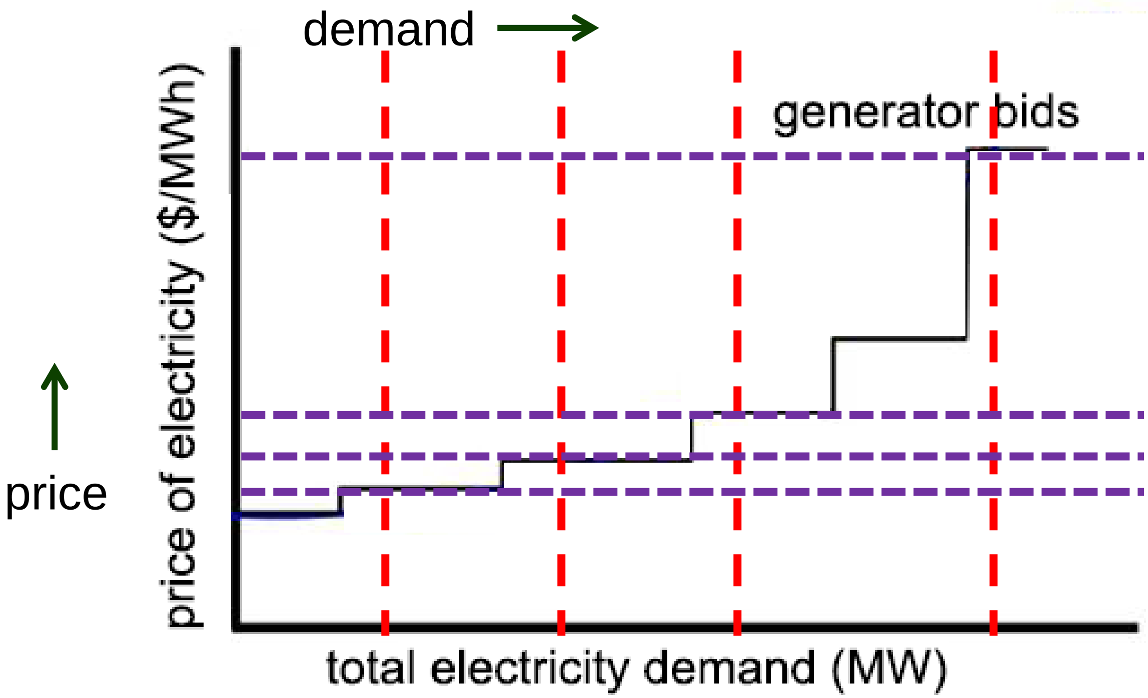
Traditional Bulk Power System



transmission level

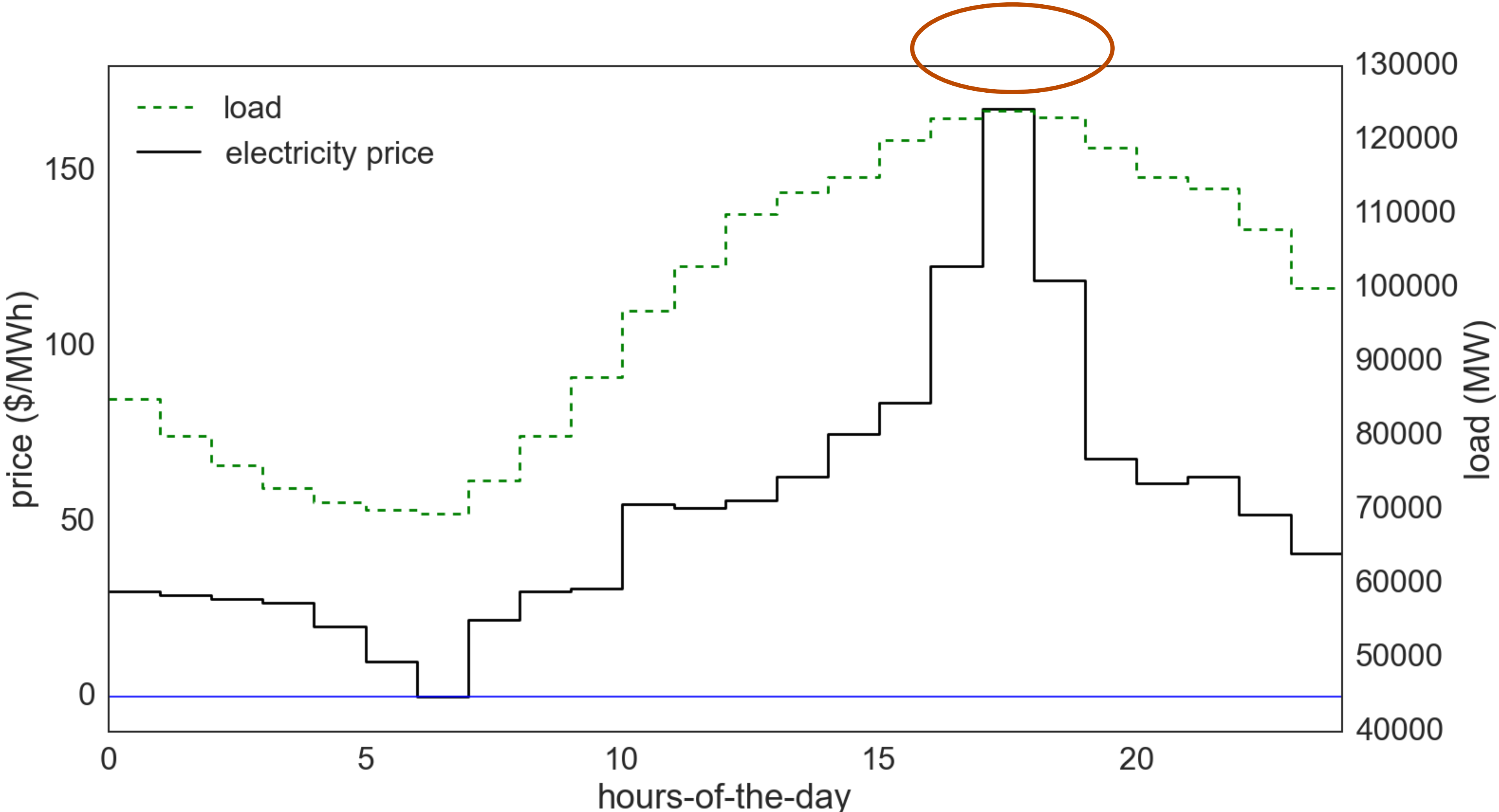
distribution level

Bulk Power Market



- owners of generators bid into the bulk power market
- as demand increases, more expensive generators are needed to meet the demand

Example Variation of Price

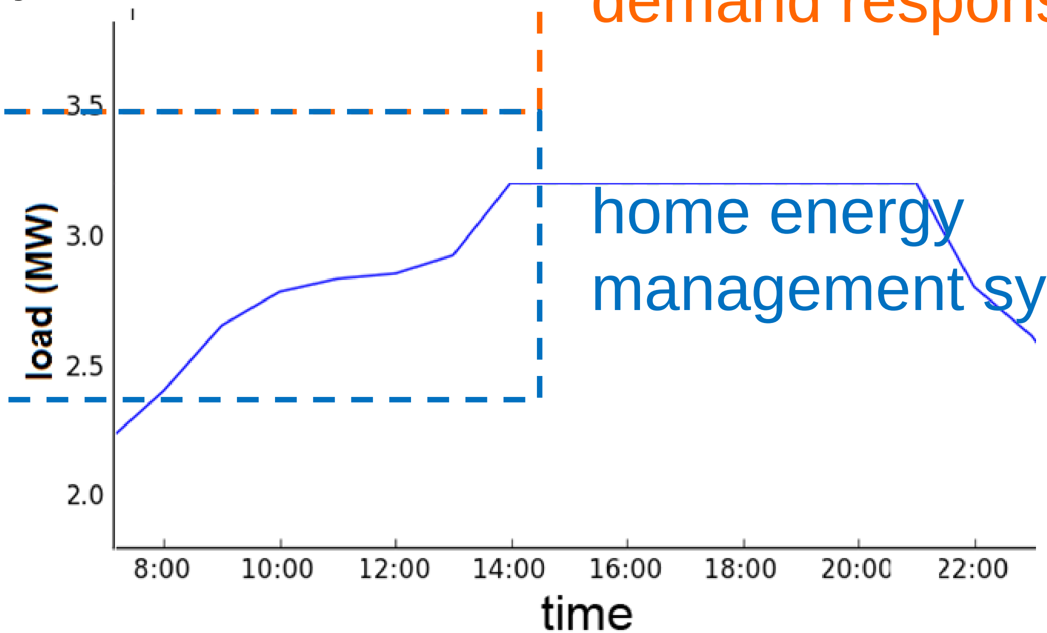


Demand Response

- **demand response:**
  - peak demand reduction by shifting or shedding loads in response to system or economic conditions
- **load shedding:**
  - demand is removed from the system
- **load shifting:**
  - electric energy consumed by a load (e.g., electric vehicle charging) is moved from one time (e.g., peak) to another
  - total energy consumed is approximately the same
- sample demand response (DR) programs:
  - direct load control (DLC)
    - air conditioner
    - electric
  - time-varyi
    - real-tim
    - time-of-

aggregator-based demand response

home energy management system



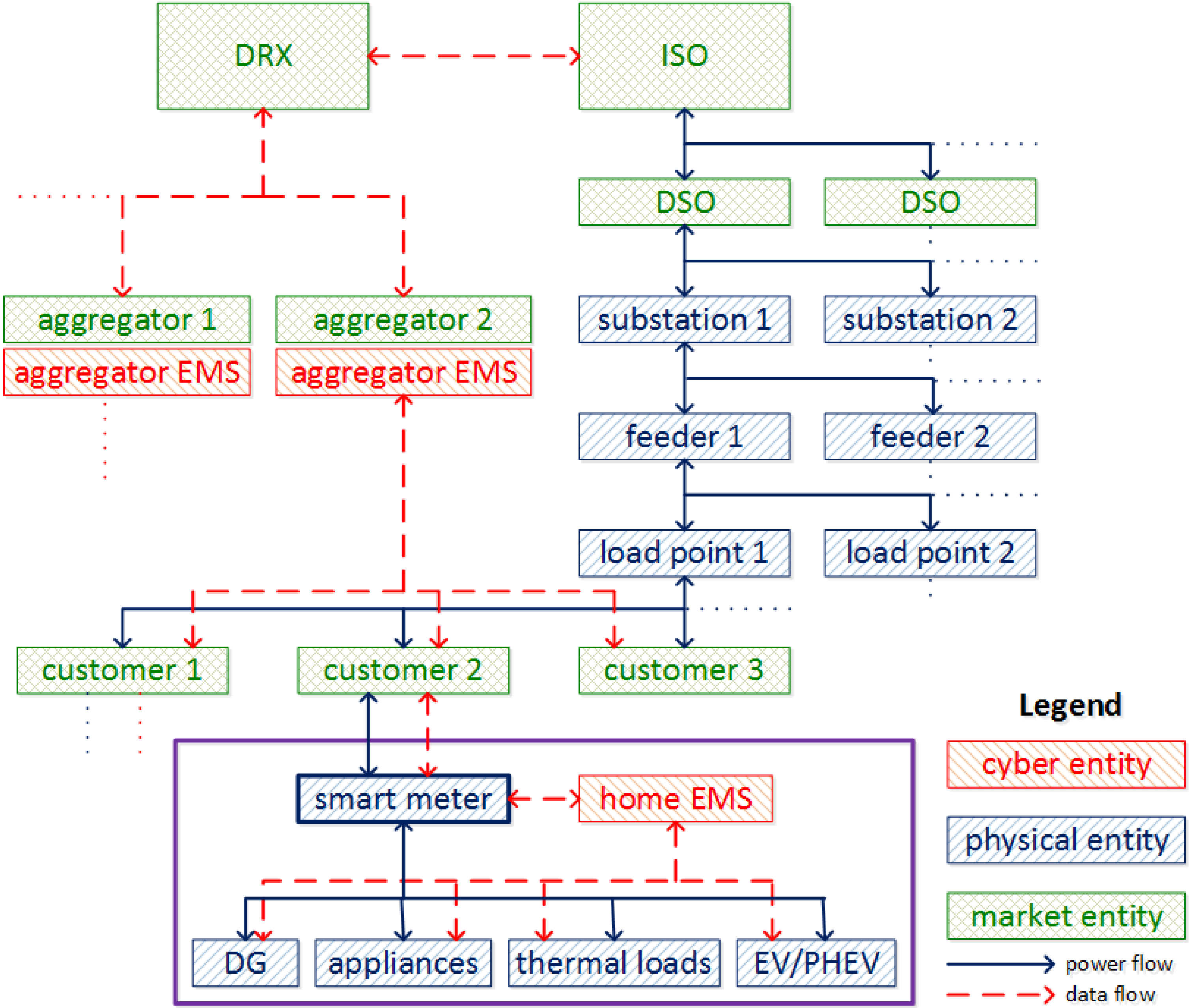
Motivation for Demand Response

- physical
  - growth in transmission capability lagging behind growth in peak electricity usage
  - residential electricity sales in the United States expected to grow 24% between 2011 and 2040
  - peak demand expected to exceed available transmission capability

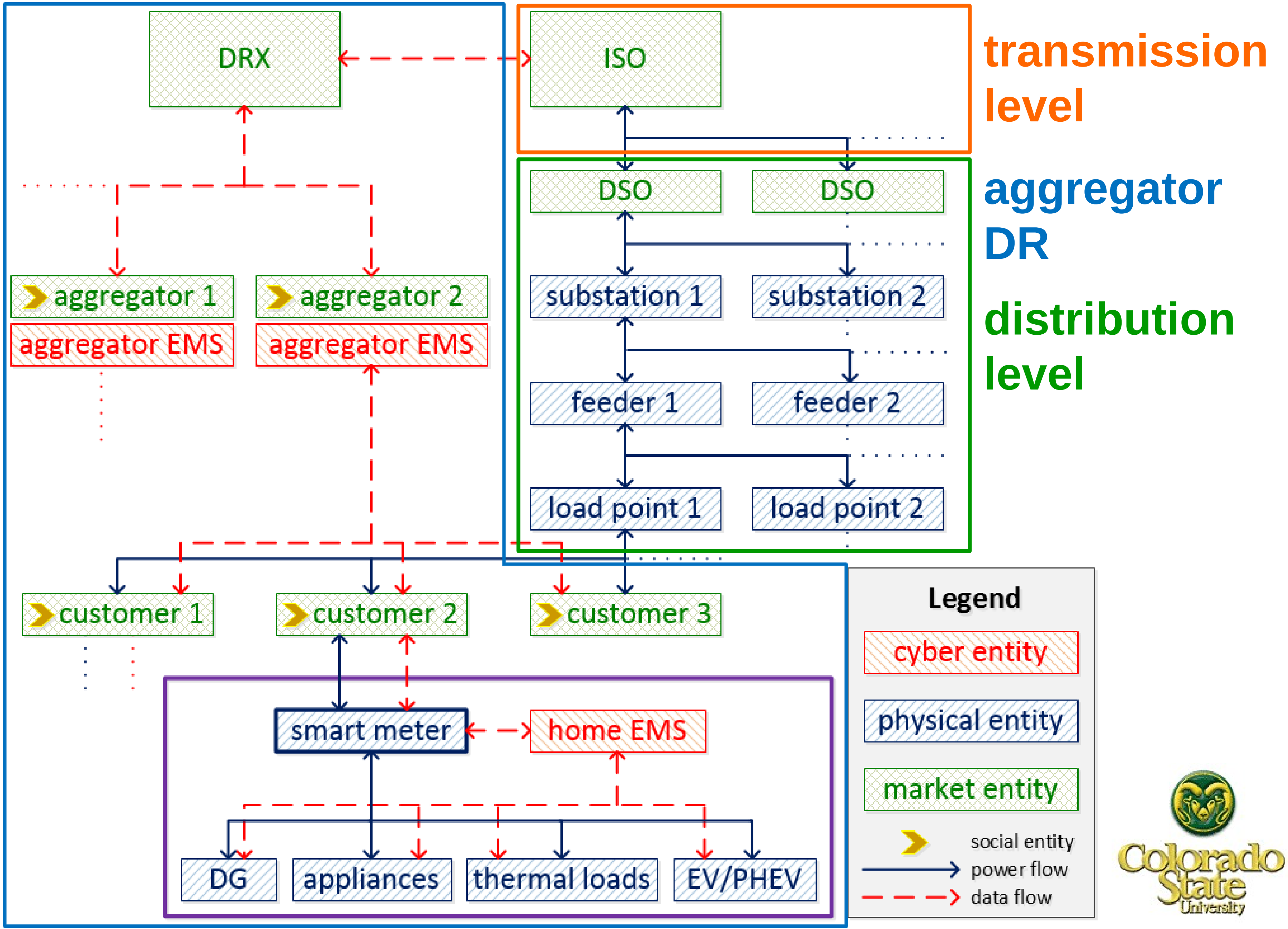
- economical
  - peaking power plants are expensive
  - *5% reduction* in peak demand during the 2000 California energy crisis would have *reduced wholesale prices by 50%*

- intelligently reducing load during peak hours would help alleviate these problems (i.e., using demand response)

Cyber-physical System

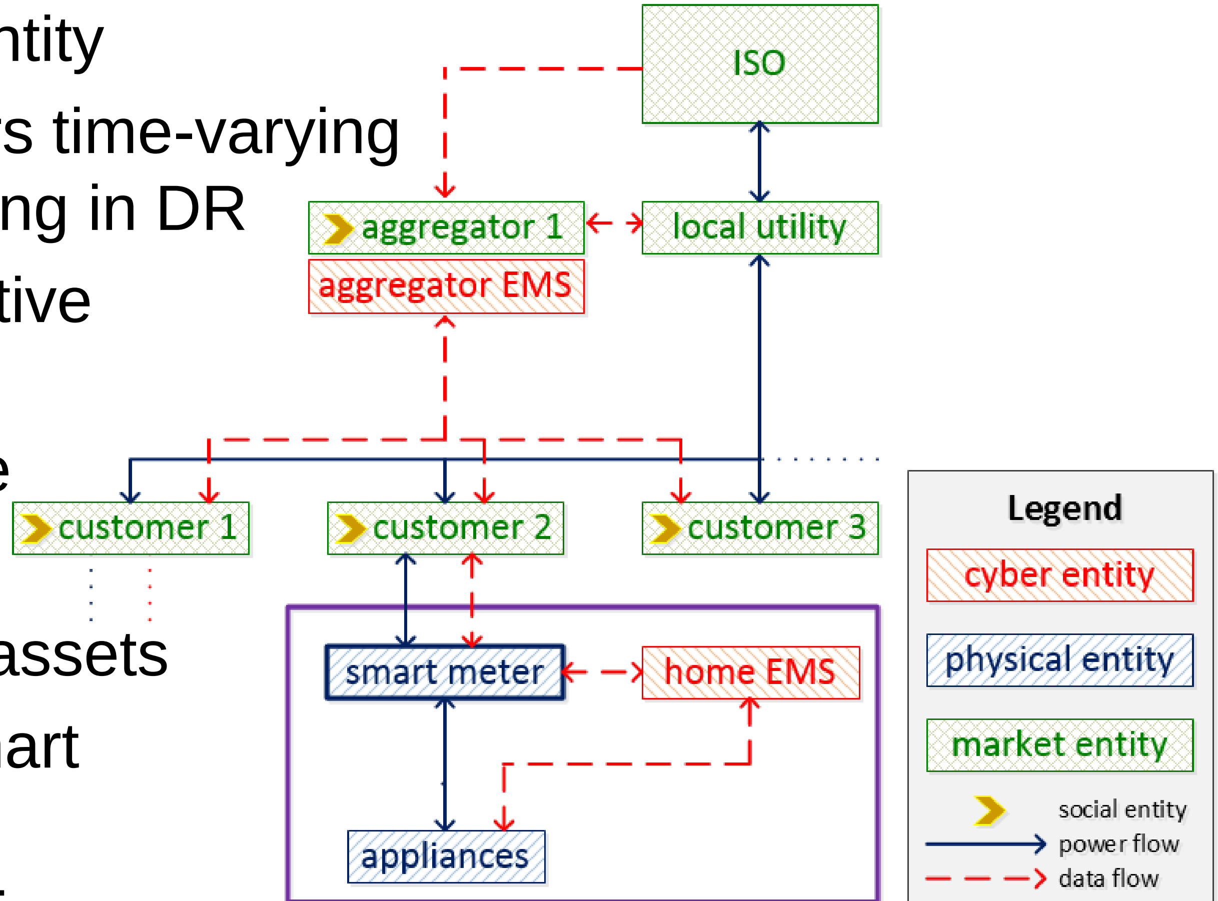


Cyber-physical Social System (CPSS)



Aggregator-based Residential Demand Response

- for-profit aggregator entity
  - offers all customers time-varying price for participating in DR
    - customer incentive price (CIP)
    - competitive rate
- customer
  - owns a set of DR assets
    - schedulable smart appliances
  - pays CIP for allowing aggregator use of DR assets
    - generally cheaper than utility price



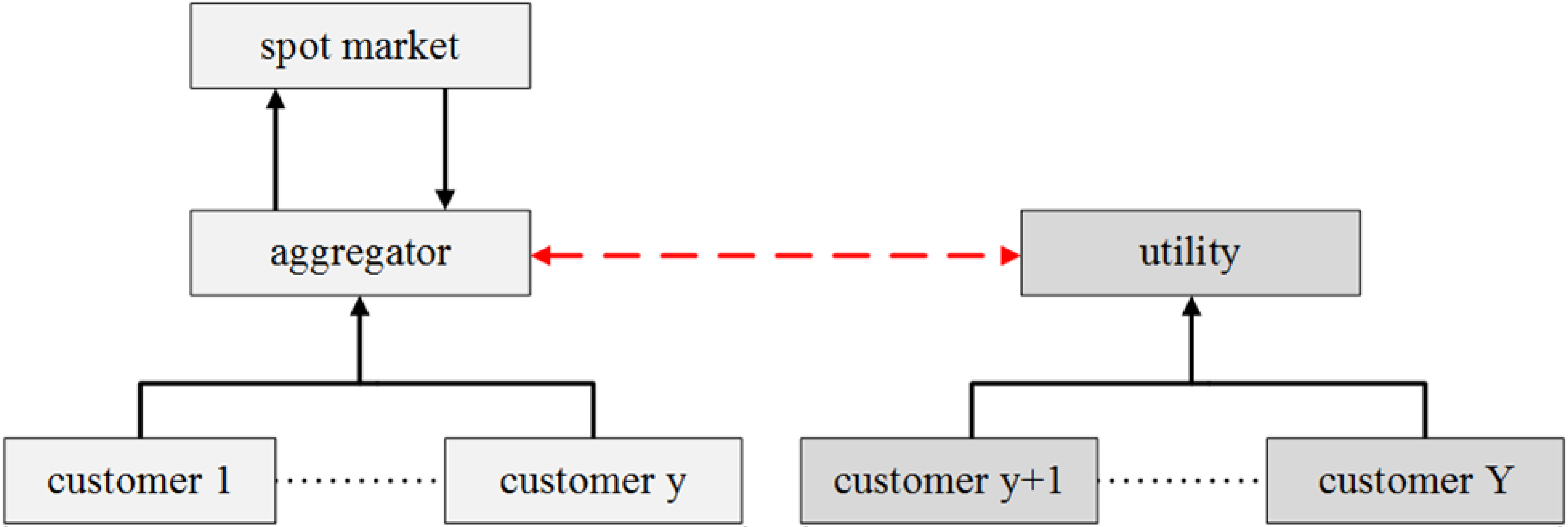
Assumptions

- price is exogenous
  - at the load levels one aggregator changes, bulk price changes marginally
- retail electricity market is fully deregulated
  - allows customer to choose supplier
- control and communication infrastructure
  - exchange of information and control of DR assets
- customer willingness to participate

Smart Grid Resource Allocation

- Smart Grid Resource Allocation (**SGRA**)
- given
  - set of customers
  - information about customer loads
- constraints
  - customer constraints
    - availability of loads to be rescheduled
    - incentive pricing requirements
  - system
- objective
  - aggregator find *customer incentive pricing* and *schedule of loads* to maximize aggregator profit
- hypothesize that optimizing purely for profit, a beneficial change on the peak load will be enacted

System Model – Aggregator-Customer-Utility



- aggregator determines incentive pricing for *all* customers
  - day-ahead using forecast spot market and dynamic pricing
- customer decides whether incentive price worth inconvenience
  - customer 1 to y decide it is worth it
  - customer y+1 to Y decide it is not worth it
- aggregator and utility need some relationship

Enabling Technologies and Assumptions

- retail electricity market is fully deregulated
  - allows customer to choose supplier
- control and communication infrastructure
  - exchange of information and control of schedulable loads
- customer willingness to participate

Heuristic Framework Overview

- SGRA solved using a heuristic framework, implemented as a genetic algorithm
- designed as a day-ahead optimization
  - optimization technique needs to run in less than 24-hours
- resolution of framework of 15-minutes
  - i.e., 96 intervals of 15-minutes to represent the day

Framework – Schedulable Loads

- subset of the system load is schedulable
- aggregator possesses information of each schedulable load
  - the runtime duration
  - average power rating
  - the initial customer scheduled start time
  - load availability vector

- information provided by customer for each of their schedulable loads

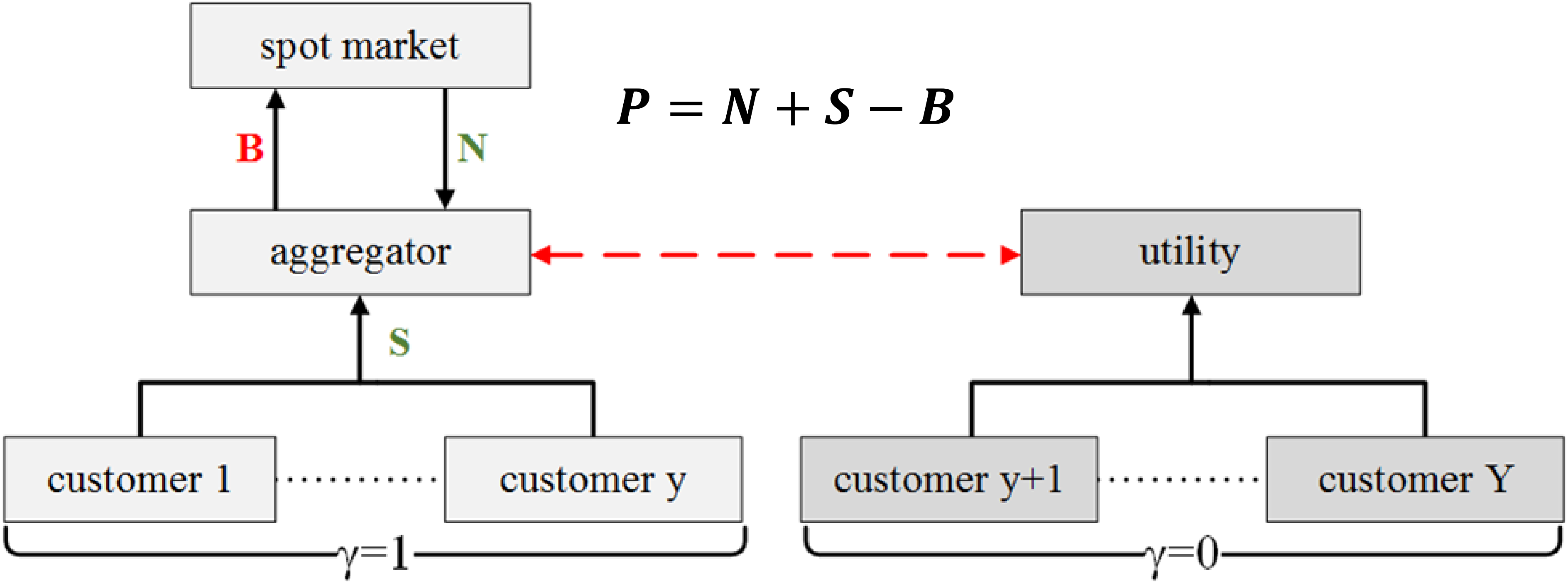
Framework – Aggregator

- additionally, aggregator possesses information on:
  - the forecasted spot price in the bulk electricity market
  - the forecasted dynamic price from the distribution company
  - an indication of whether a customer will allow their load to be rescheduled to a given time with a given incentive price

- aggregator must determine the following to maximize their profit:
  - the set of loads to attempt to reschedule
    - customer can still say no
  - the rescheduled start time for each of the loads
  - the customer incentive pricing vector
    - 96 price points for each of the intervals of the day

Framework – Objective Function

- let $\boldsymbol{P}$ be the aggregator profit
- let $\boldsymbol{N}$ be the total *income received* for selling negative load to the spot market
- let $\boldsymbol{S}$ be the total *income received* for selling electricity to customers at the incentive price
- let $\boldsymbol{B}$ be the total *cost paid* to the spot market for buying electricity



$$\boldsymbol{P} = \boldsymbol{N} + \boldsymbol{S} - \boldsymbol{B}$$

Genetic Algorithm Implementation

- chromosome represents an entire solution to the problem

λ_1	λ_2	…	λ_{96}	$t_{1,sch}$	$t_{2,sch}$	…	$t_{I,sch}$

customer incentive pricing — schedule of loads

- elitism used to maintain the best solutions between generations
- selection via linear bias function
  - linear bias of 1.5 → best solution 50% greater chance of selection than median solution

```
initialize population
order population by   P = N + S – B
repeat
    select two chromosomes via linear bias
    crossover creating two new chromosomes
    mutation
    insert children chromosomes
    trim the two worst performing chromosomes
until stopping criterion
return  best chromosome
```

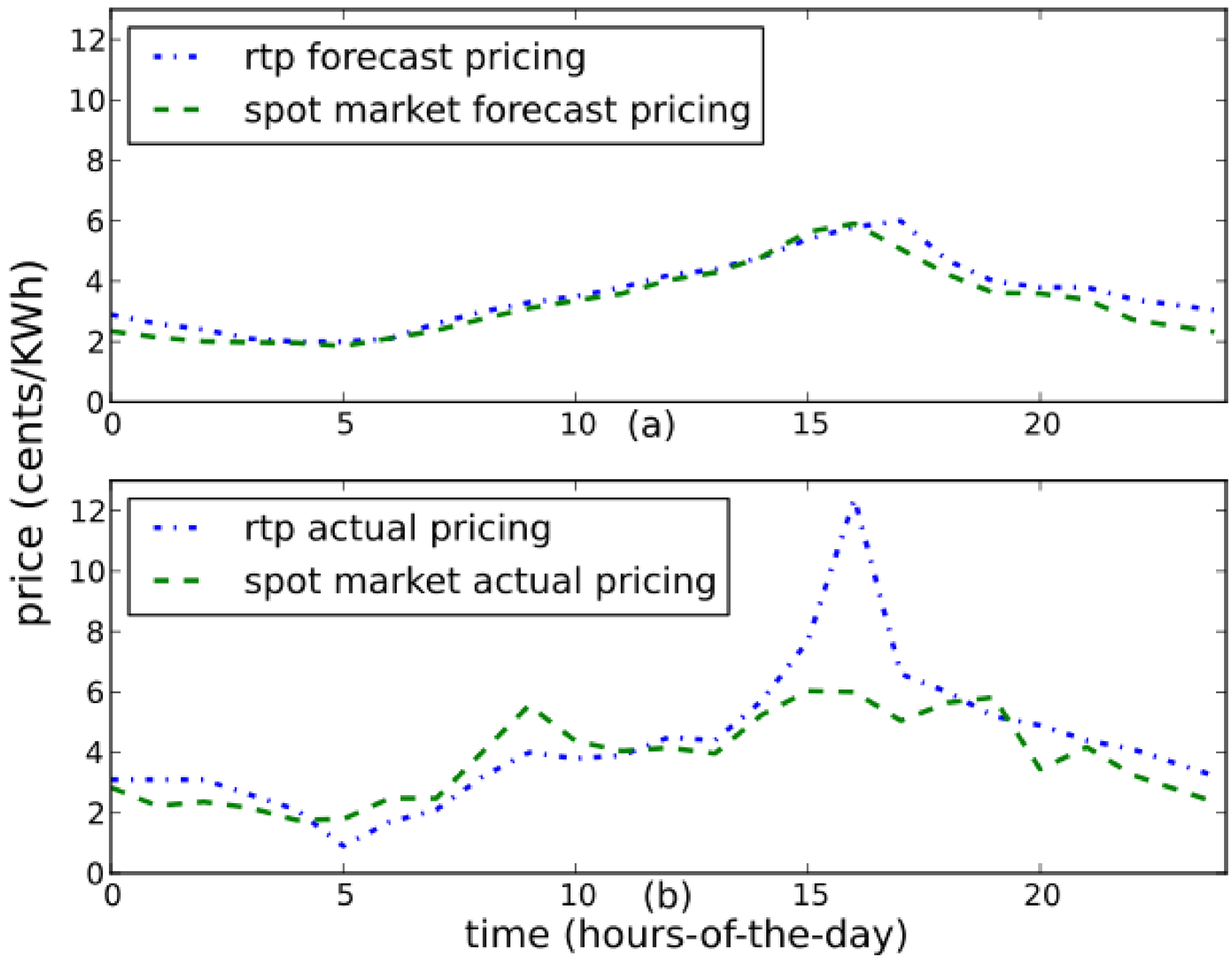
Genetic Algorithm Parameters

- parameter sweep determined parameters to use in the scope of this problem

- population size: 100
- linear bias: 1.4
- probability of mutation: 0.05
- stopping criterion: 500,000 iterations
    - ~12 hour runtime on old simulator

Pricing Data

- spot market pricing from PJM
- real-time pricing from ComEd
- pricing data obtained for Saturday July 9, 2011



Customer overview

- each customer has sets of baseline and schedulable loads
- customer participation is a key enabler in DR
  - needs in-depth study for full characterization
- behavior of each customer modeled using the α-model
  - determines if a customer will allow rescheduling ($\gamma = 1$)
  - customer can veto aggregator's schedule by setting ($\gamma = 0$)

Customer behavior: α-model

- based on an associated threshold metric for customer comfort
- metric specified for each schedulable load, i
- let
  - α_i be threshold metric assoc. with schedulable load i
  - $c_{i\text{-}0}$ be original cost of running load i at utility RTP
  - $c_{i\text{-}sch}$ be rescheduled cost of running load i at aggregator CIP
- for ($\gamma = 1$)
  - $c_{i\text{-}sch} \leq \alpha_i c_{i\text{-}0}$ must hold
- using CIP: customer always guaranteed to save $(1\text{-}\alpha_i)$ times the cost of running load i compared to paying utility RTP

Customer behavior: α-model

- customer inconvenience of load rescheduling capture by γ
- To generate α values, we use coefficient-of-variation (*cov*) based method
  - Analogous to generating task execution times for a heterogeneous set of machines
- let
  - μ_a be desired average load α value for all loads
  - σ_a be desired *cov* of load types
  - σ_c be desired *cov* of customers within a load type
- for each load type, k,
  - a gamma distribution is sampled with (μ_a,σ_a) to obtain mean α_k value, denoted $\mu_{a,k}$

Customer behavior: α-model

- for each customer that owns load type, k,
  - obtain α_i by sampling a gamma distribution with (μ_{ak}, σ_c)
- this gives similar α values for each load type, k
  - thus, similar customer behavior
- this approach is chosen due to assumption that customers will generally act similar regarding use of a certain load type
  - TVs v. laundry machines

Customer loads

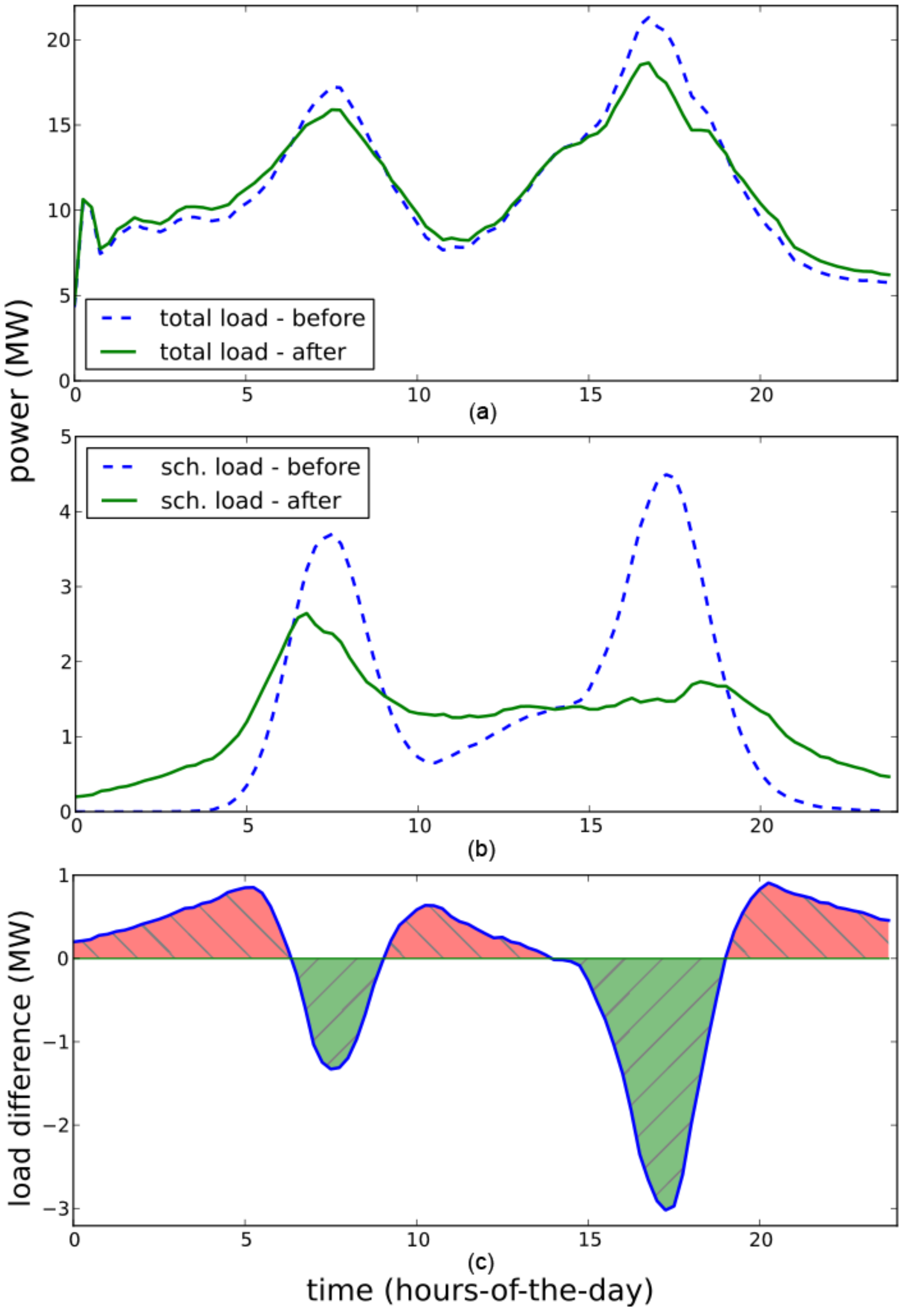
- each customer has two sets of loads
  - baseline: thermal (AC and EWH) and other non-schedulable loads
    - non-schedulable loads are probabilistically generated from data
  - smart (schedulable): chosen probabilistically from 18 generic appliance types
    - if present, rated power, start time (obtained from normal distribution) and duration in 15-min blocks
  - each load has an assoc. availability window (A_{i_start}, A_{i_dur})
  - t_{t_start} is original start time
  - to generate availability window for each load i, $A_{i\_dur} = U(\delta i, 96)$ is generated around t_{t_start}

Simulation Setup

- 5,555 customers
  - each customer has a threshold for determining whether the CIP offers enough discount
  - each customer defines a time period to which each load can be rescheduled
- 56,498 schedulable loads
  - probabilistically generated to simulate use of an average household
  - each load has an availability window around its original start time that it can be rescheduled to
- pricing data
  - bulk power spot market price from PJM
  - utility price from ComEd
- genetic algorithm used as optimization method

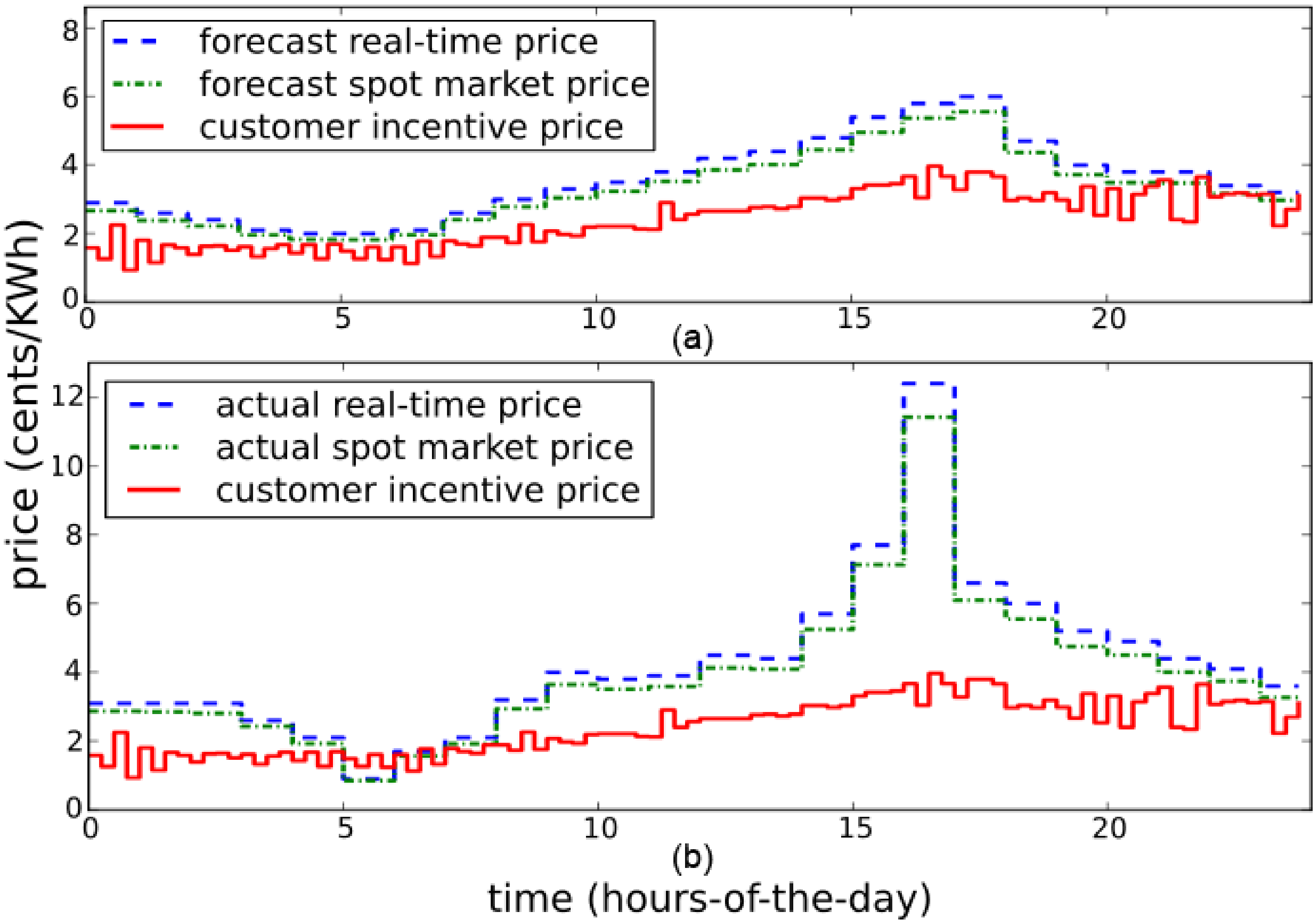
Results – Demand Response Load Shifting

- peak reduction of 2.66MW (12.6%)
- aggregator profit
  - $947.90
- total customer savings
  - $794.93



Customer Incentive Pricing

- CIP versus forecast price (top) and actual price (bottom)



Contributions

- alternative customer pricing structure
  - *customer incentive pricing*
- heuristic optimization framework
  - mathematical models for the customer and aggregator entities
- large-scale test simulation consisting of 5,555 customers and ~56,000 schedulable loads
  - used real pricing data from ComEd and PJM

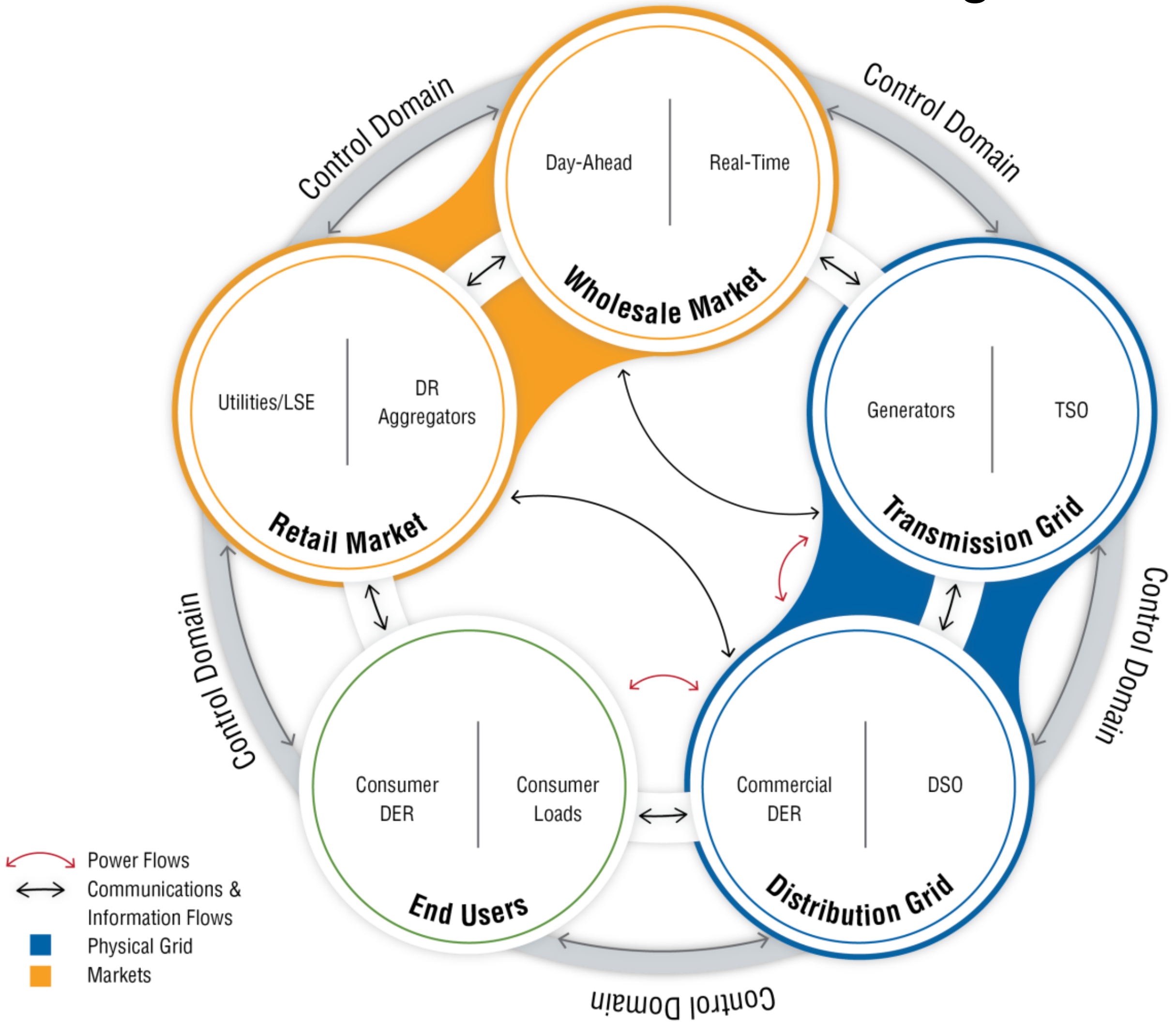
- showed that aggregator optimizing for economic reasons:
  - benefits participating customers
  - benefits aggregator
  - benefits *non-participating* customers
    - system peak reduced as a common good

Some research challenges

- how to integrate distribution systems and transmission systems in power systems simulations?
  - **co-simulation framework**
- how to verify and validate if method of DR is effective?
  - **visualization techniques**
  - **Use of high-performance computing platforms for extended simulations**

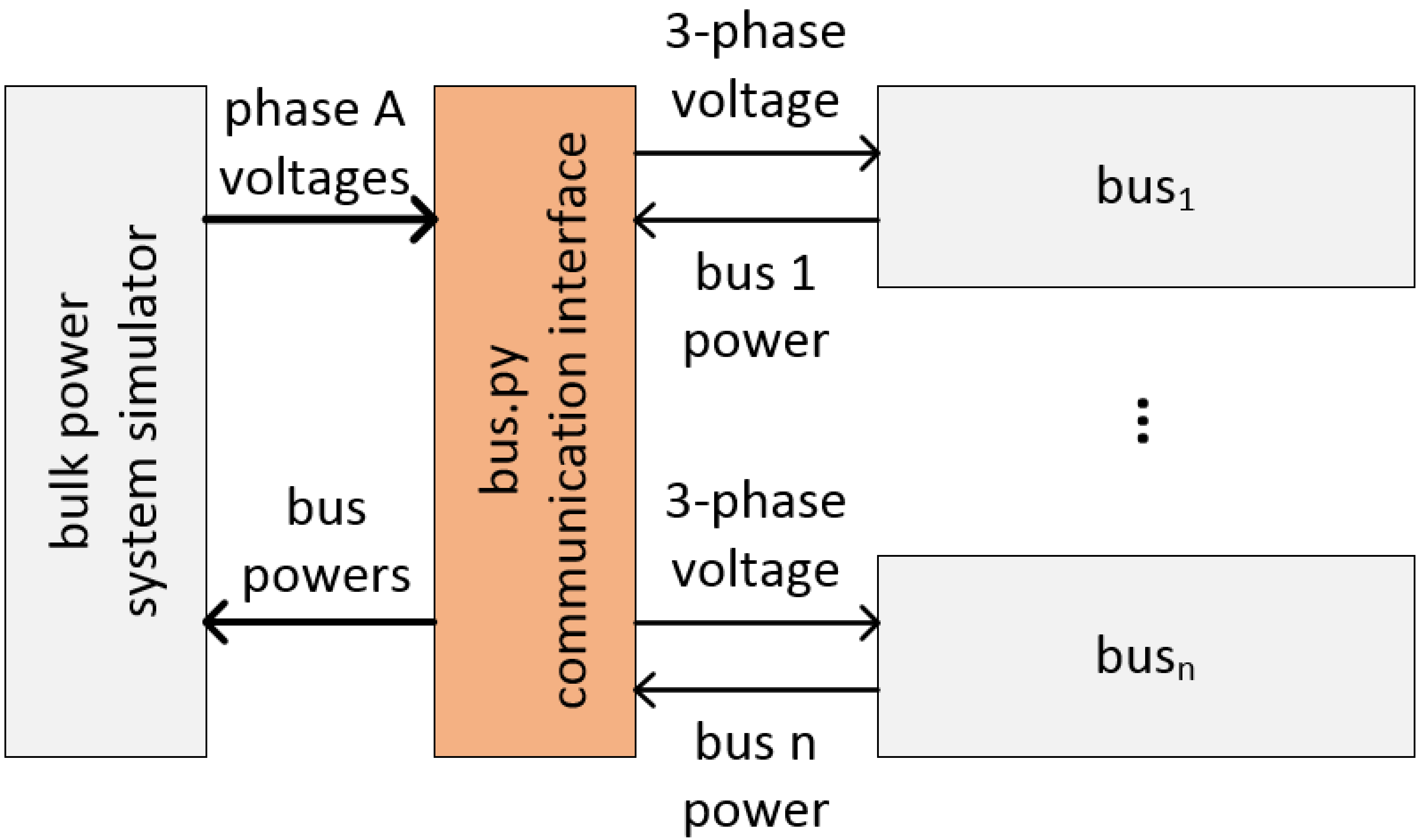
Co-simulation in Power Systems

- **co-simulation:** multiple individual tools, each specializing in a specific domain, interact while running simultaneously



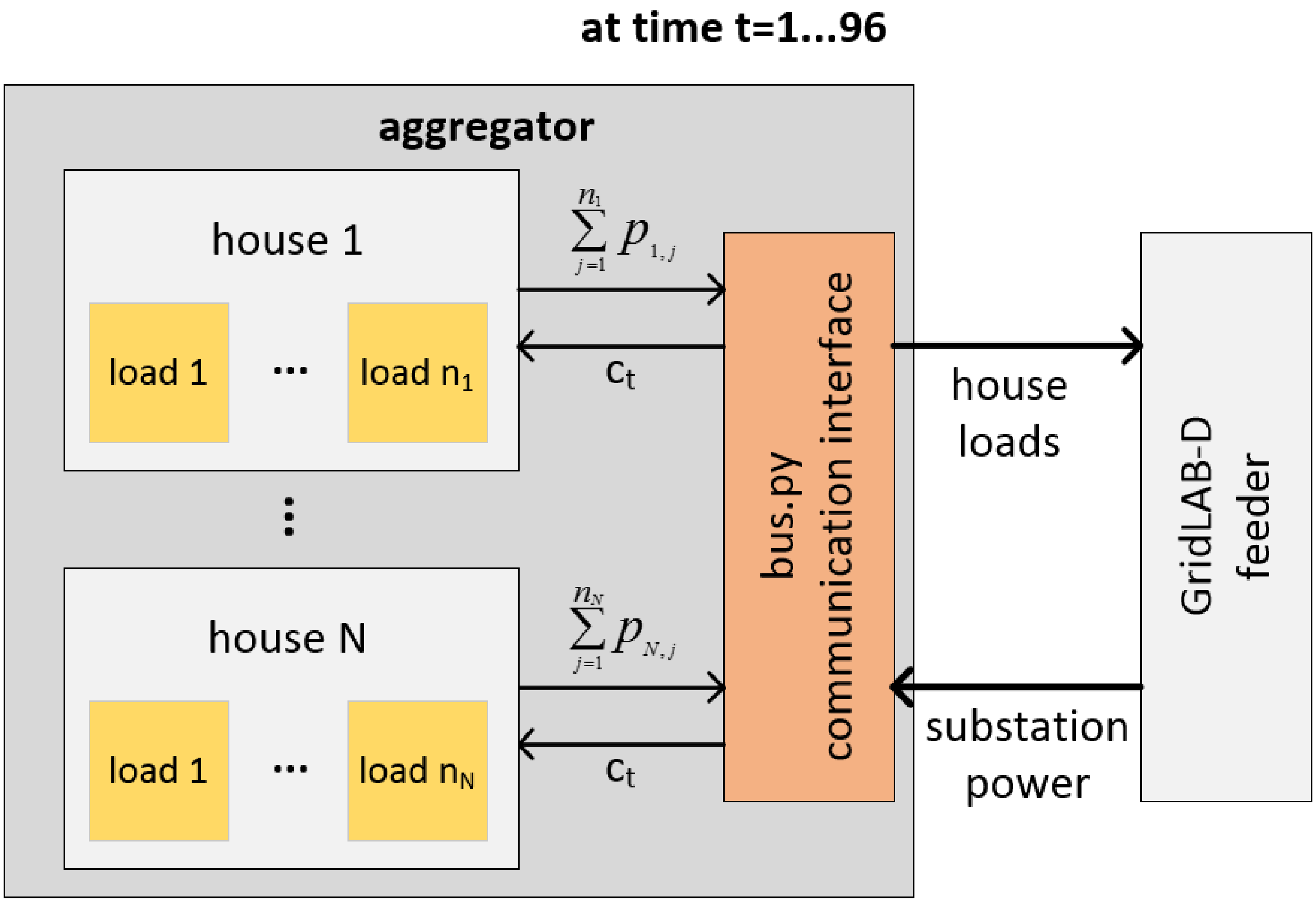
Bus.py

- introducing bus.py – a transmission-level bus simulator and communication interface
- enables co-simulation between:



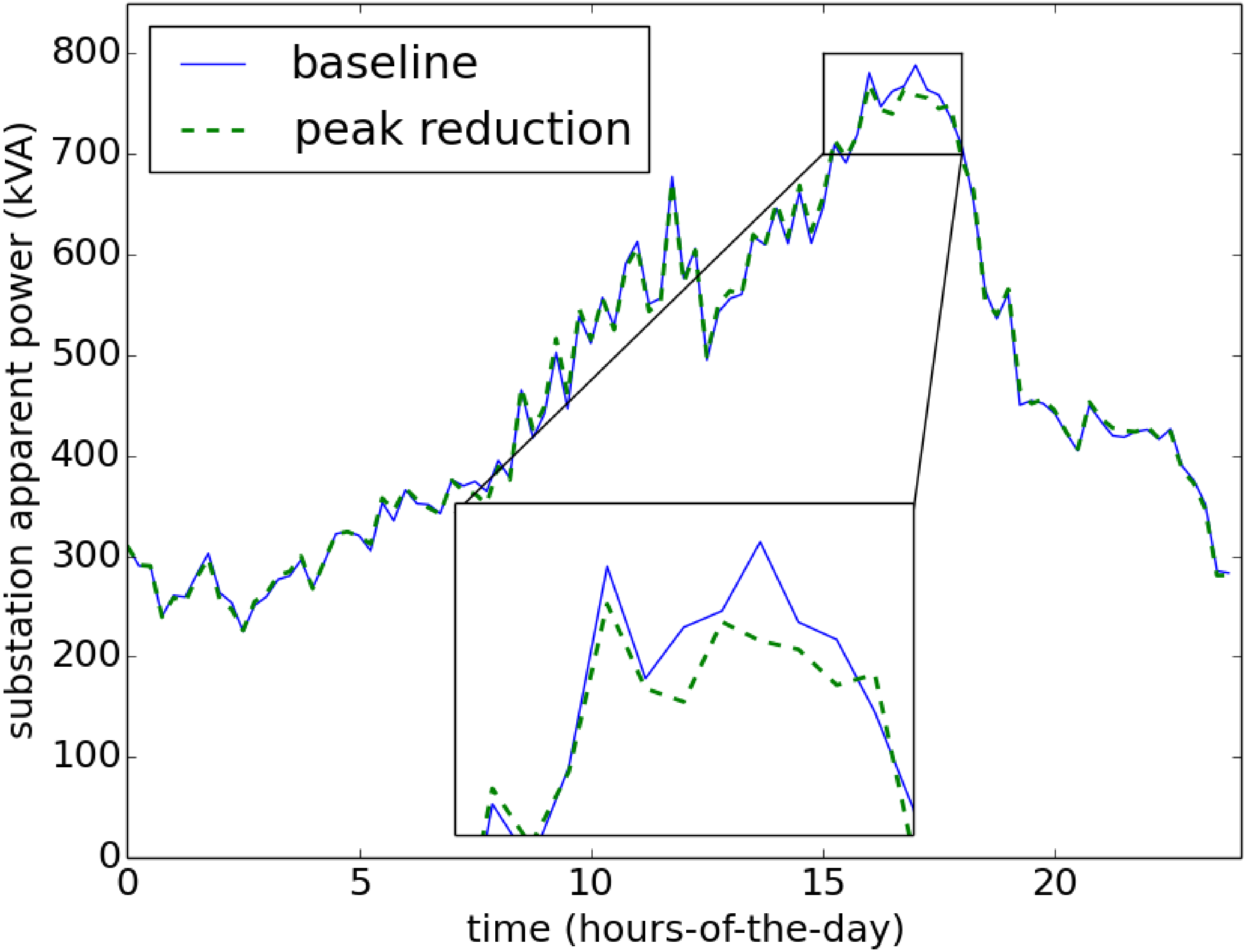
System Model

- aggregator controls the individual loads within a household
- each house is represented on a GridLAB-D distribution feeder
  - GridLAB-D – a PNNL distribution system simulator



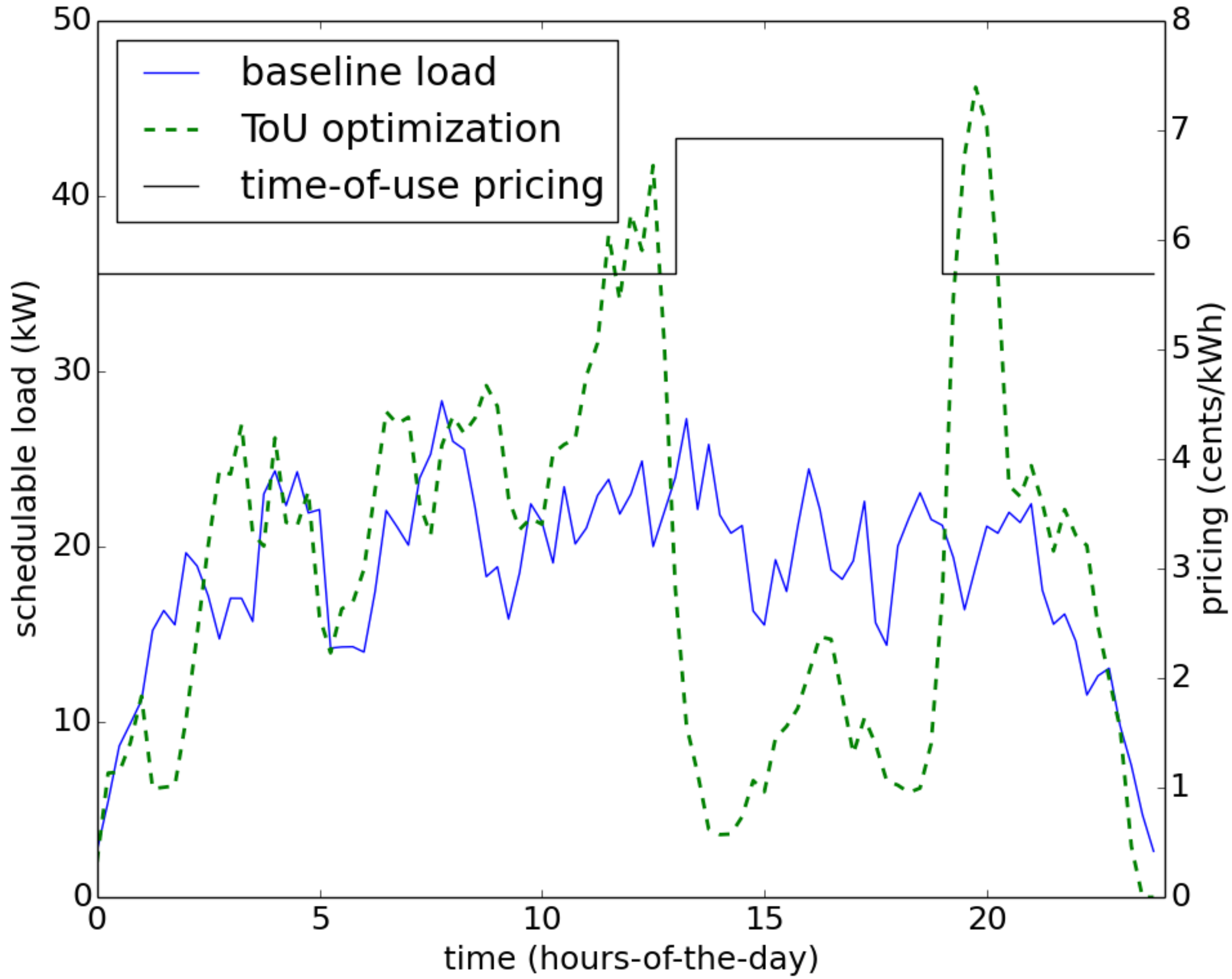
Peak Load Reduction

- reduction in peak load of 19.2 kVA (total available at peak time)



Cost Minimization in Time-of-Use Pricing

- change in schedulable load when minimizing cost in a time-of-use market



Contributions

- design of bus.py, a software transmission bus interface for use in Smart Grid co-simulation studies
- demonstration of bus.py interfacing with GridLAB-D simulating a small set of customers on a distribution feeder and an aggregator entity

Conclusions

- resource allocation in Smart Grid
  - system-view with aggregator-based demand response
- the demand response method using customer behavior model shown to reduce peak demand
- reduction in peak demand can:
  - reduce the cost of electricity
  - reduce the output of dirty diesel peaking generators
  - defer building new transmission lines
- future work on
  - surveys-based quantification
  - delayed-gratification techniques for customer profits

Questions and Discussion

- collaborators:

Hansen et al., “Heuristic Optimization for an Aggregator-based Resource Allocation in the Smart Grid,” IEEE Transactions on Smart Grid, Vol. 6, No. 4, pp. 1785–1794, July 2015.

Hansen et al., “Bus.py: A GridLAB-D Communication Interface for Smart Distribution Grid Simulations,” in Proc. *IEEE Power and Energy Society General Meeting 2015*, 5 pp.