# DIRECT LOAD MANAGEMENT OF ELECTRIC VEHICLES

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# Outline

- Why is electrical vehicles (EV) scheduling important?
- Background work
  - Traditional dispatch and load forecasting
  - Smartgrid: Pricing and Direct load Management
- Proposed Architecture
  - Arrival model for EVs
  - Load characterization
  - Optimal load dispatch
- Numerical results
- Conclusions

# Electrical Vehicles

- Electric vehicles (EV) entering the market later this year
  - Few or no emissions and allow to reduce the dependency on oil ☺
  - High Wattage loads for the network ☹
- Like in other networks, the distribution of energy is limited by congestion, in two forms
  - Generation capacity congestion
  - Transmission capacity congestion
- Generation dispatch is based on load prediction
  - It is handled through standard system identification and time series analysis (e.g. ARMA, ARIMA models) – 10%

# What is the load?

- It is a complex signal, in power systems called complex phasor, around the 60Hz frequency
  - The complex envelope of the power drawn from a “bus” that is the termination of a transmission line

$$L(t) = \underbrace{L_Q(t)}_{<0} + jL_I(t) = V(t)I^*(t)$$

- It is not really generated from a single system with an input, it is is a very mixed bag of things
  - Contributions generated by automata – EV is a special case
  - Contributions by a dynamic systems (Refrigerators, Heaters, Air conditioners)

# Motivation of this work

- Smartgrid efforts
  - Making the load visible – Smart metering
  - Making the load controllable – Smart Demand Response and Demand Side Management
- EVs are likely to have onboard embedded intelligence and communications
  - They can  be “smart-loads” that can be directly controlled
  - Interrupting charge is not appropriate as it wears down the batteries
  - We assume once on the load cannot be interrupted – hence all we can do is schedule it
- How (do we tell a computer to do it)?

# Demand side management (DSM) and demand response (DR): background

- Priced Based Load Control
  - Time Of Use: predetermined but variable rates during the day
  - Real-time prices: cheapest way of managing demand, requires communication of a price signal → Needs an Automated System → Home Energy Management Systems
- Load Control Through Curtailment
  - Interruptible Load Programs
  - Devices like ACs are signaled to turn off for a pre-determined interval from a central control center

# Drawbacks of pricing

- Problems with TOU
  - Designed years beforehand – no actual real-time control over demand
  - While TOU is a major step in the right direction it is not designed for volatile loads
- Problems with RTP
  - Not actually real-time: prices have to be delivered to the customer beforehand to allow some planning time
  - What is the right price?
  - Feedback loop due to customer response → rebound peaks
  - Needs extensive knowledge about customer

# Drawbacks of load control

- Problems with Load Curtailment?
  - Not a market based program – cannot bid into any market
  - Only good for appliances that **can be interrupted** (ACs or water heaters) or in emergency situations to avoid involuntary cascaded blackouts
- Possible Solution?
  - “Transective” Direct Load Scheduling = Optimize the schedule based on price and safety constraints

# Key Idea: Unbundle the load

- The load can be decomposed in two parts

$$L(t) = L_S(t) + L_T(t)$$

Smart EV Load    Traditional Load

- EV arrival process (non-stationary Poisson process) + charge

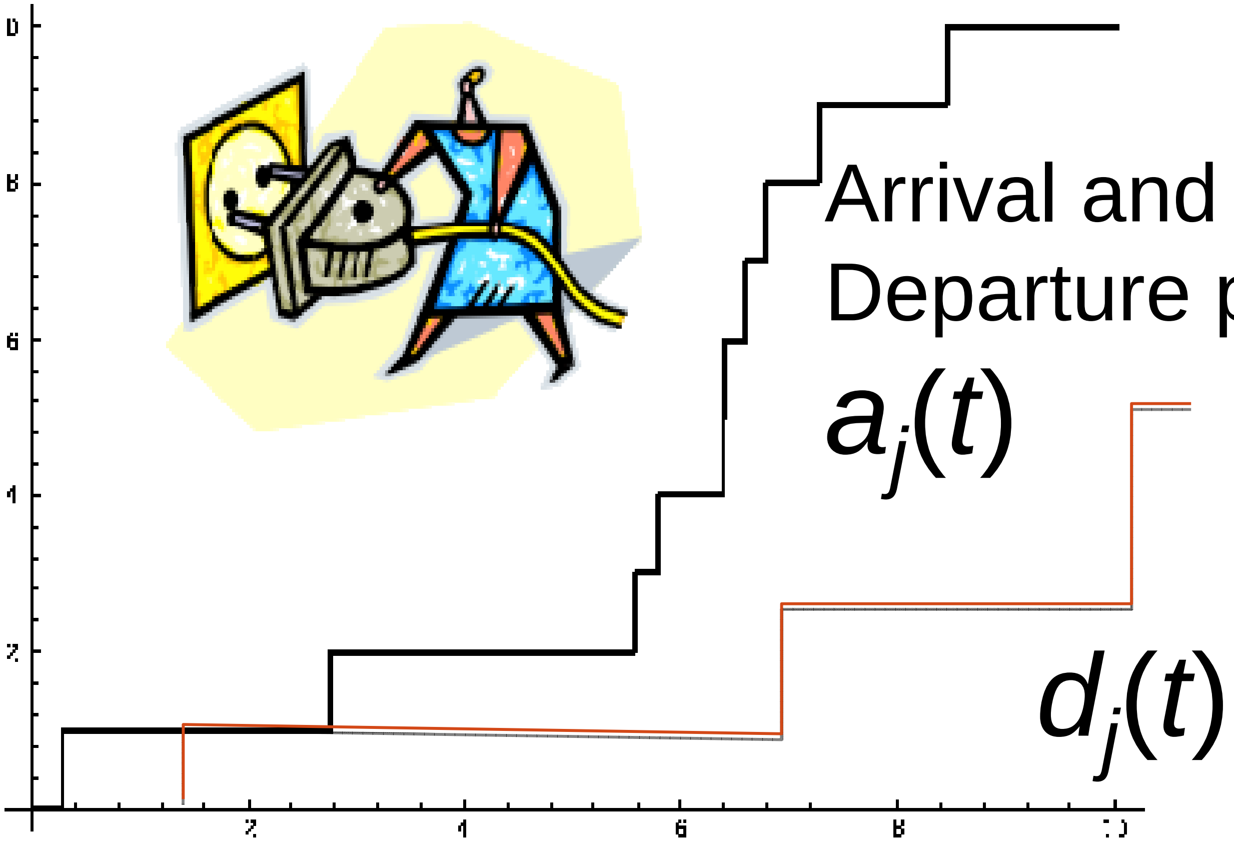
$$a(t) = \sum_i u(t - t_i^a) \qquad C_i \;\; i.i.d. \sim f(C)$$

$$t_i^d \geq t_i^a$$

- EV scheduled load: optimal

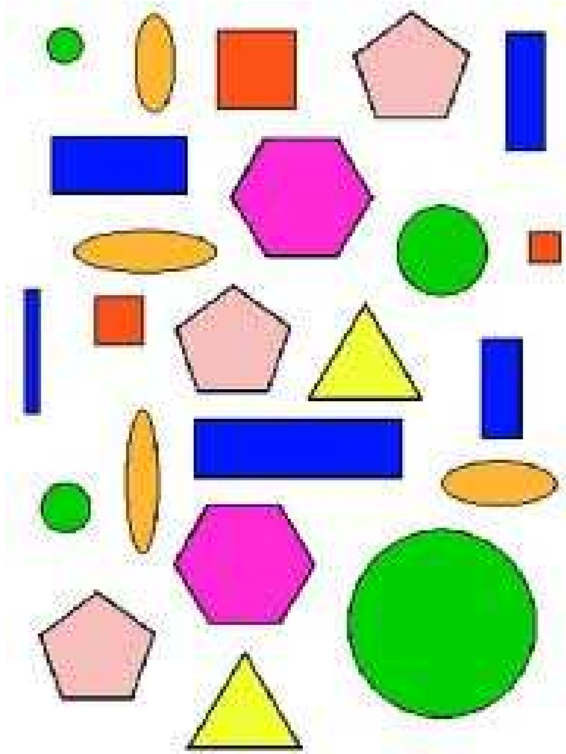
$$L_S(t) = \sum_i rect\left(\frac{t - t_i^d}{C_i}\right)$$

# Goal: Mapping requests in queues into planned injections power



# Digital Direct Load Scheduling: Step 1 - analog to digital load mapping

- Goal: Find a tractable model to communicate control information and reassemble the optimal load process
- Communicate arrival time and charge request $(t_i^a, C_i)$
- Quantize
  - Quantize time of arrival (use side information on message arrival)
  - Quantize charge
- Example: Electric Vehicles – $C_i$ is a scalar representing the hours of battery charge needed
  - 4 bits, 16 classes give > 10%

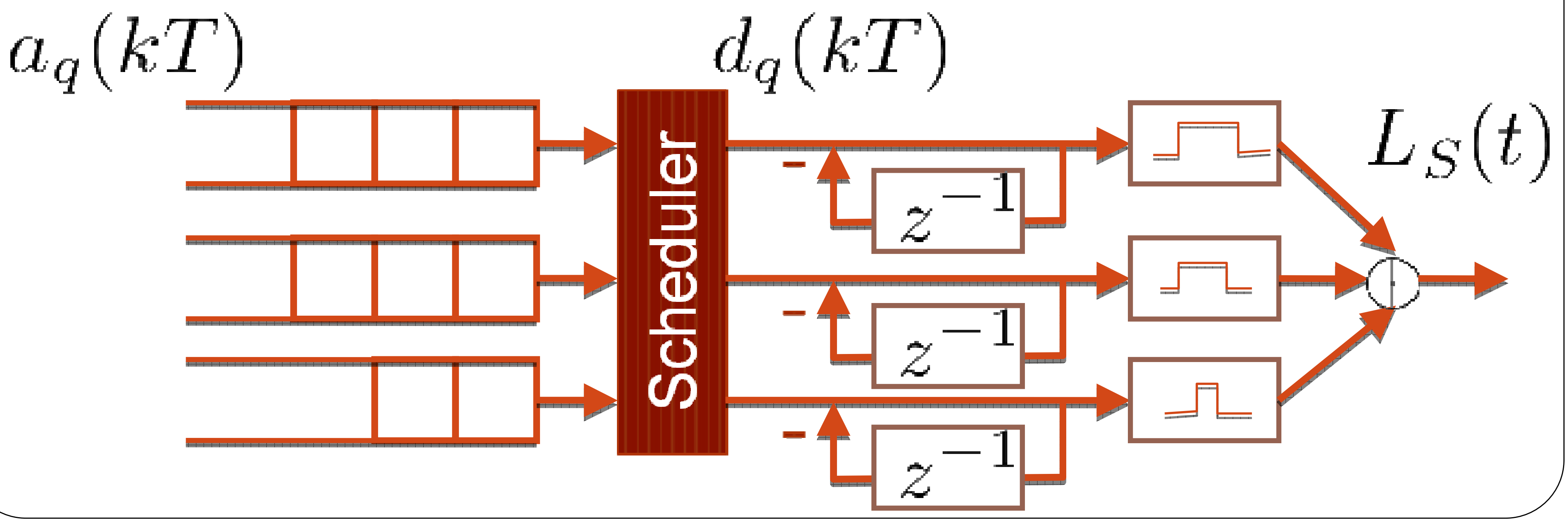


# EV scheduling

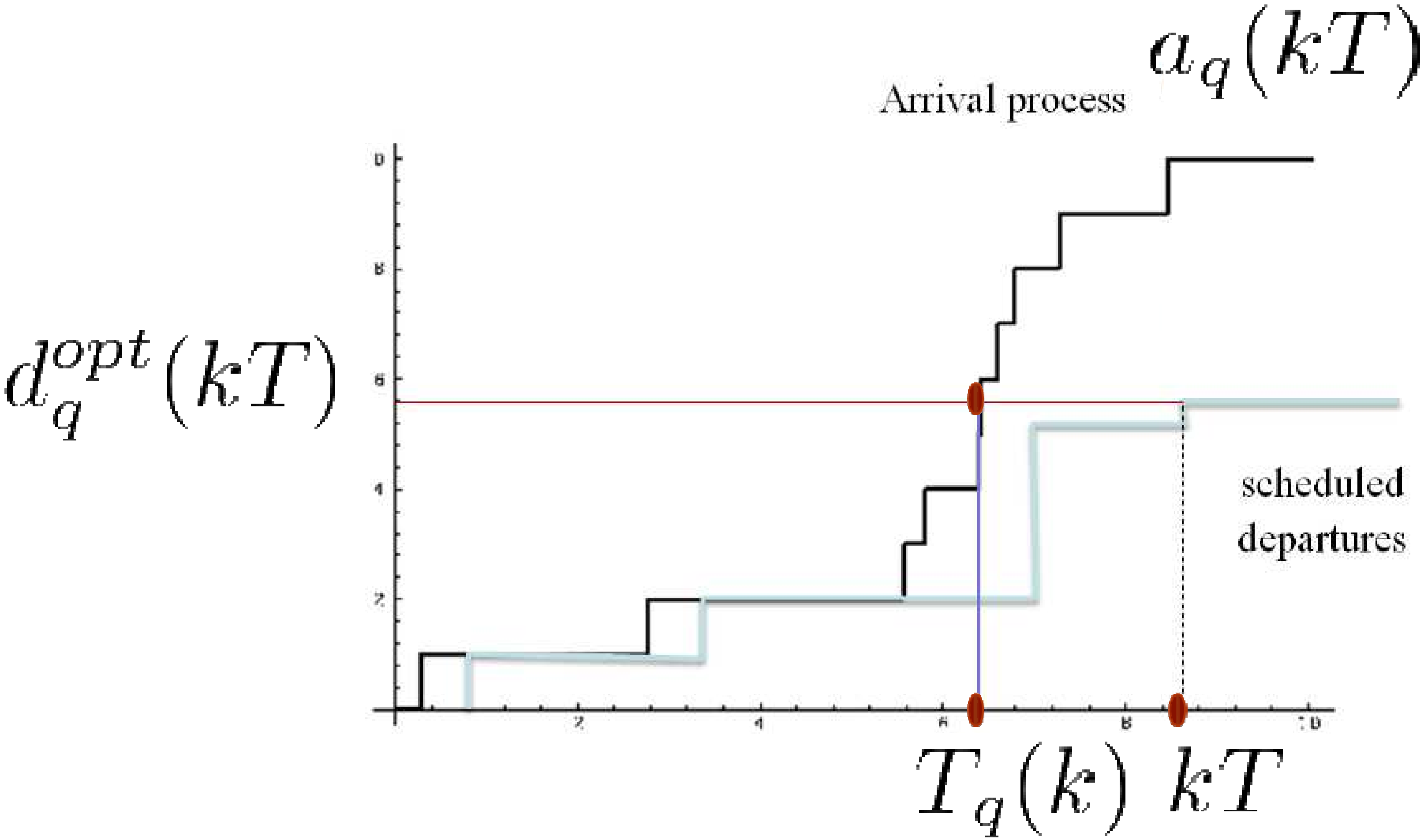
- Quantize requests

$$\hat{C}_i = Q(C_i) \quad \hat{C}_i \mapsto q_i \in \{1, \dots, Q\}$$

- Place them in queues depending on the quantized charge value $q_i$



# Feedback




$$T_q(k) = \max\{n \leq k : a_q(nT) = d_q^{opt}(kT)\}$$

# Control Layers

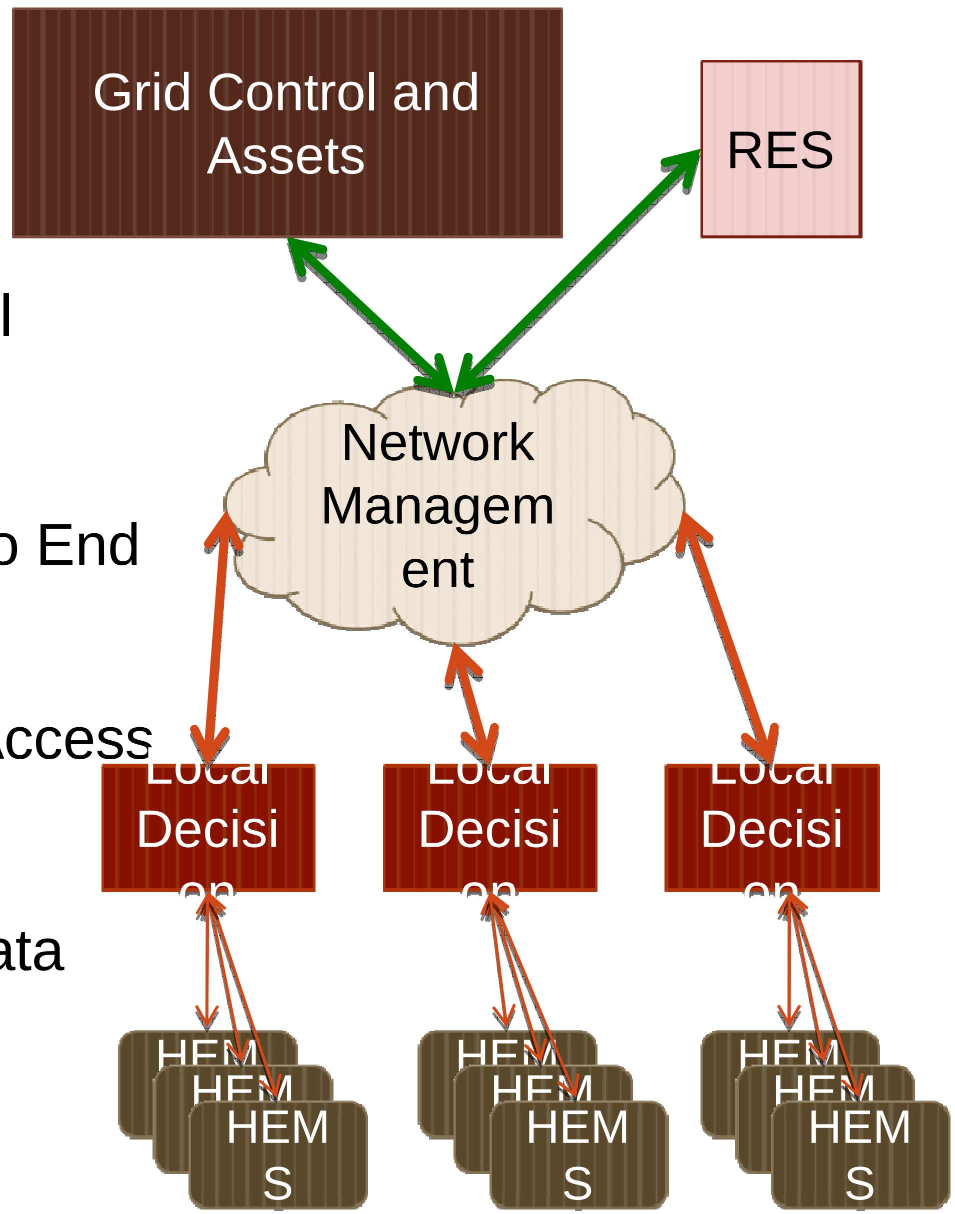
Transmission assets and control
Renewable Capacity

Network Management Layer – End to End

Local Decision and Control Layer - Access

Digital Direct Load Scheduling - Data

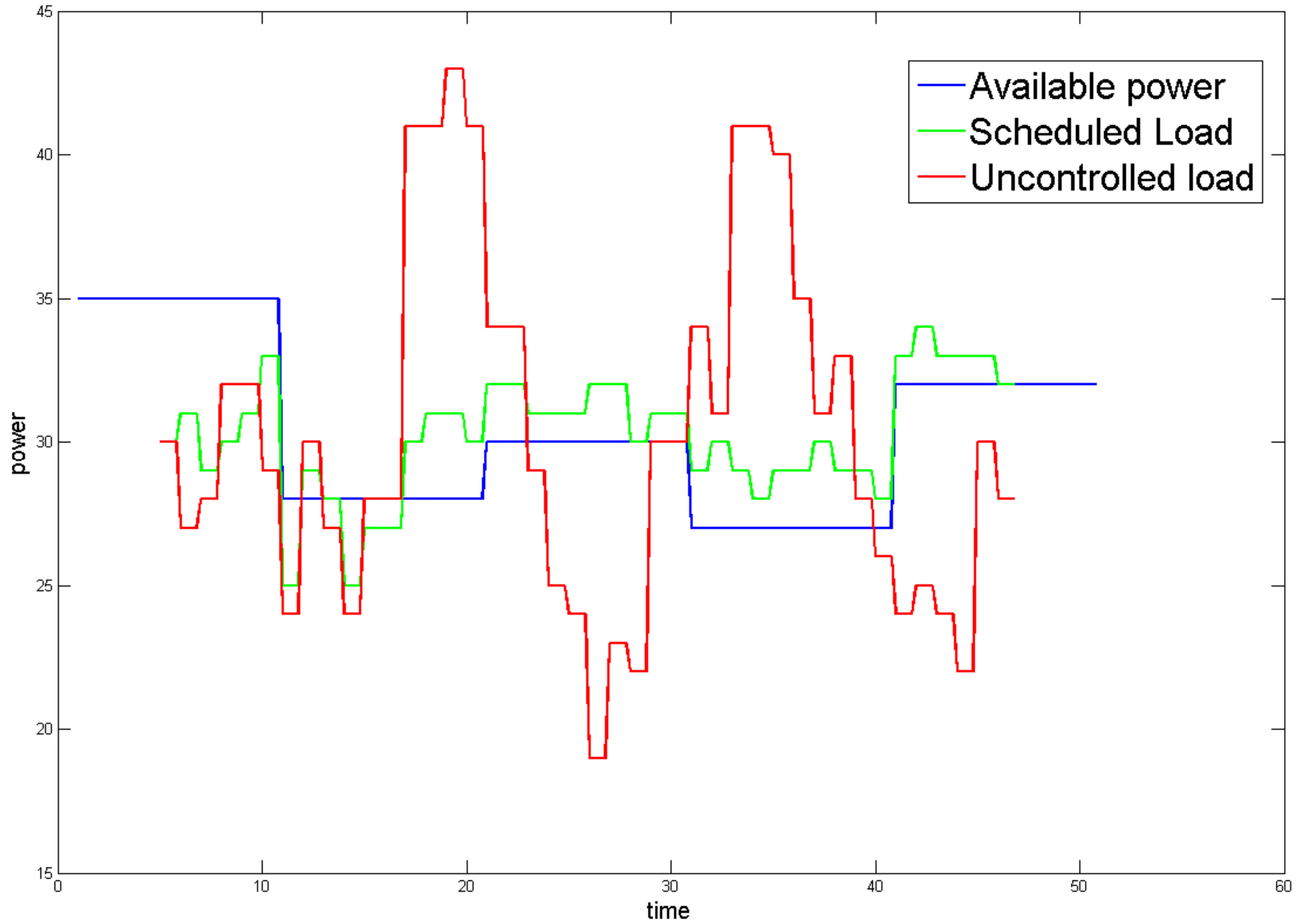
Physical Load Layer



# Preliminary results

A few simulations….

# Numerical Results – Linear Programming approximation




a single type of smart appliance

$1 \leq$ Job size $\leq 4$ units of time

Arrival process is Poisson with constant rate $\lambda = 3$

Solver: one-step look-ahead rollout algorithm on a
certainty equivalent controller that uses linear programming to schedule the appliances

Look-ahead horizon = 5 units of time

For fairness, the number of scheduled appliances is equal in the two profiles and no arriving appliances is delayed beyond t = 50

%50 reduction in deviation from the generation profile

# Smart load forecasting

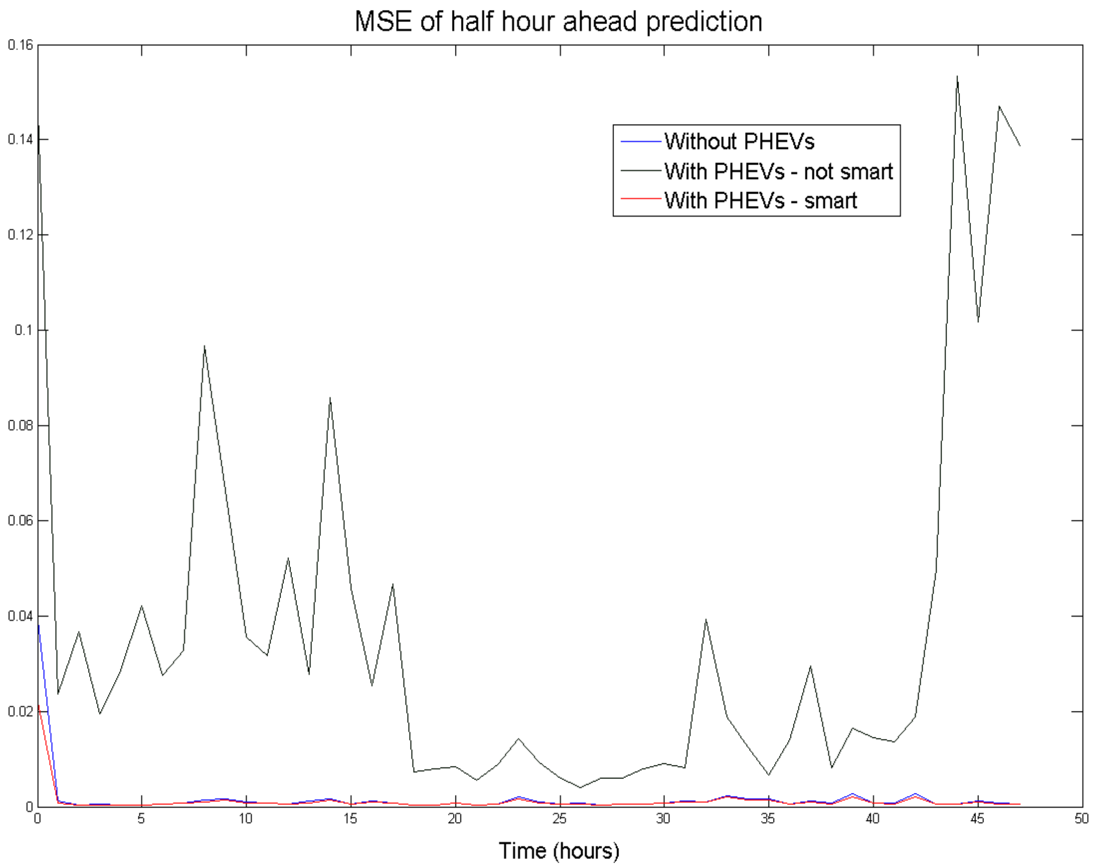
- Even if we do not control the load in a centralized fashion, observability of $L^S(t)$ will improve our short-term load forecasting ability
- Modeling future demand requires statistics of arrivals and of load profiles through $f_j(C)$
- The arrival rate $\lambda_j(t)$ is a non-stationary time-series
  - ARIMA process with multiple seasonalities
- The digital conversion of the load is a model to design an efficient encoder for load metering as well
- The rate requirement is very modest…

# Smart load forecasting (cont.)

- Short term forecast with considerable number of Smart EVs
- Number of future smart loads of type j.

$$N_j(t) = N_j^{new}(t) + \nu_j(t)$$

- $N_i^{new}(t)$ is a stochastic term but $\nu_i(t)$ is de




**EV load Parameters:**

λ(t) Doubly periodic

ARIMA $(110)(110)_{48}(110)_{336}$

EV added to load profile of substation (real data transport network normalized)

<u>CLASSICAL</u>

Load bundled, ARMA

<u>SMART FORECAST</u>

Track EV rate λ(t) ~ C(t)/T using classical ARIMA

Mt/GI/∞ model

Classical Prediction for base load

# Conclusions

- Efficient markets sail on good opportunities
- We described a method to realize efficiency for the customer by allowing the EV requests to be scheduled so that the community realizes the greatest energy efficiency
- Basic principle:
  - Unbundle and digitize the load – do not store energy, store requests!

# Thank you!!