Stochastic Simulation of Smart Electric Vehicles in Electric Power Markets

Implementing the ALM Market Framework on the Smart Grid in a Room Simulator

Jonathan Donadee[1], Martin Wagner, Hadi Amini[1,2], Marija Ilic[1], Orkun Karabasoglu[2]

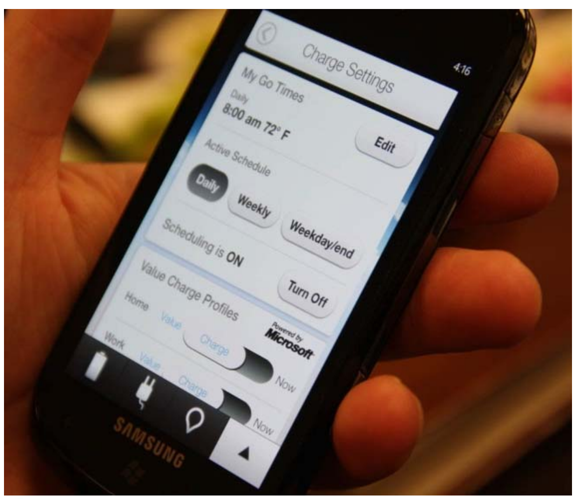
[1] Department of Electrical and Computer Engineering, Carnegie Mellon University
[2] SYSU-CMU Joint Institute of Engineering (JIE)

10th CMU Electricity Conference
Pre-conference Workshop
March 30, 2015

Background

- Electric Vehicles (EVs) have the potential to be a valuable resource to the electric grid

- EVs are a large deferrable electric load
  - EV owners don’t care when an EV charges
  - EV owners only concern is sufficient energy for driving
  - Flexibility allows “smart charging” control to achieve many objectives



Picture Source: Ford.com

Research Questions

- How can we integrate EVs into Electric Energy markets
  - Enable demand response to system conditions
  - Compensate the intermittency of renewables
  - Increase power system efficiency

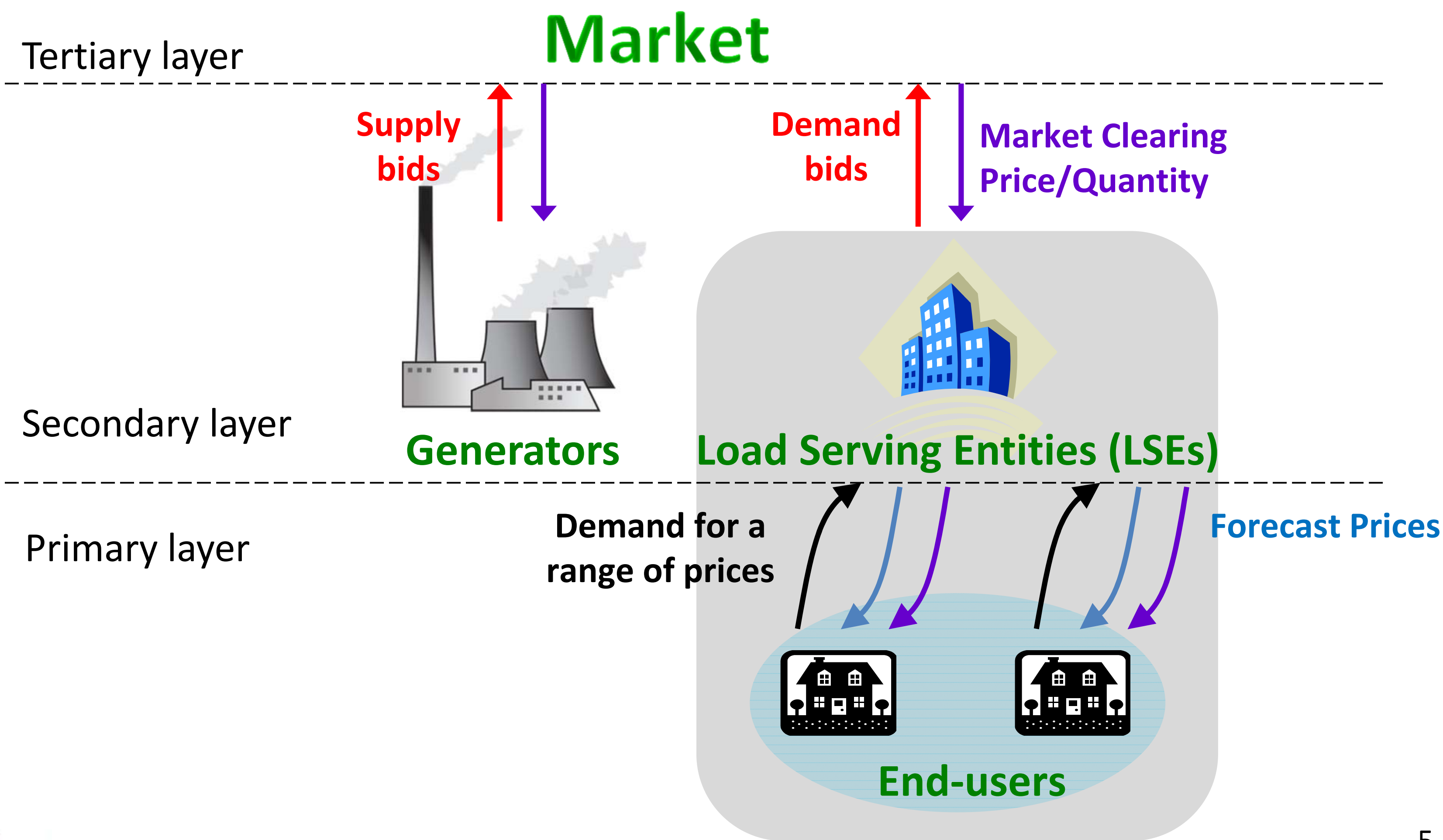
- How does the system cost or EV driver's cost depend on EV charging strategy?

- How does can data analytics improve the smart charging of self interested EVs?

Approach

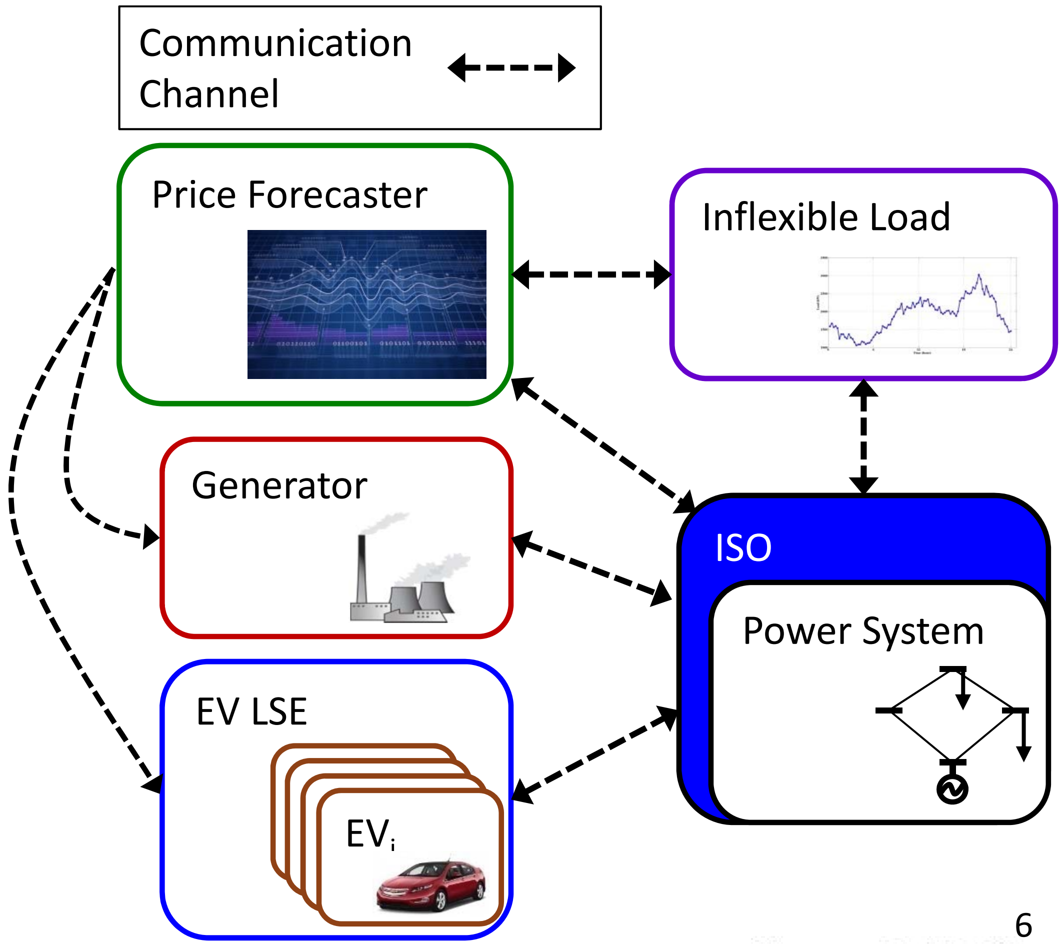
- Developed algorithms for integrating EVs into the DYMONDS adaptive load management (ALM) framework [1-4]
- Implement a stochastic simulation on the "Smart Grid in a Room Simulator" (SGRS)
- Simulate the process of online learning from data
- Evaluate costs under different EV charging strategies

Adaptive Load Management (ALM) [3,4]



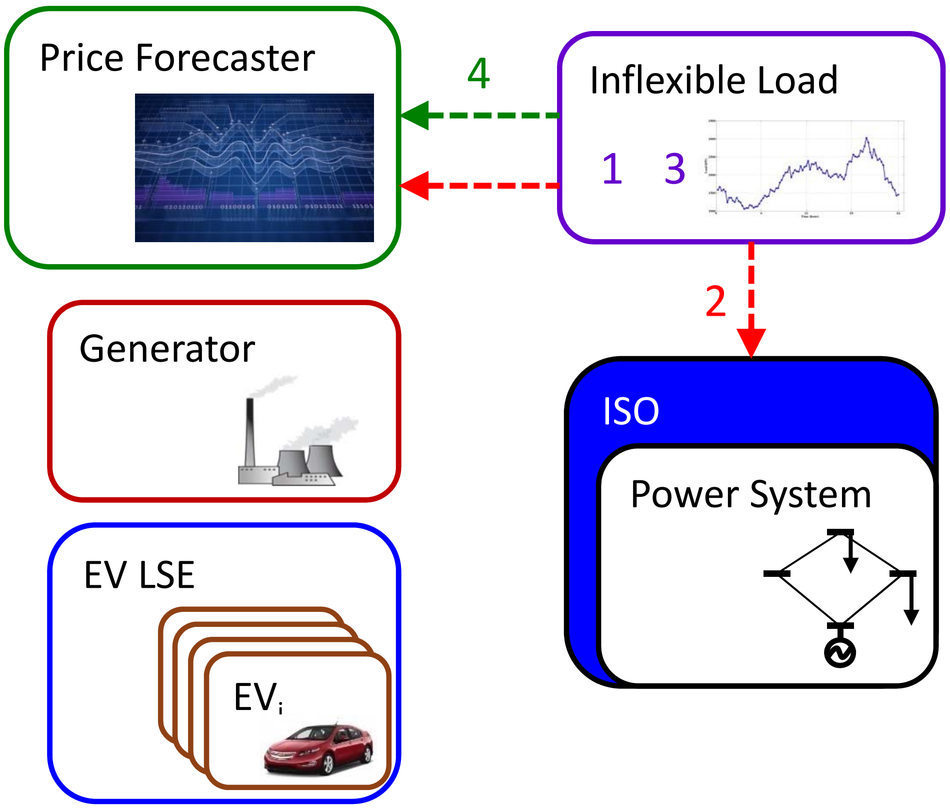
Implementation on the SGRS

- Multi-layered, interactive DYMONDS architecture
- Object-oriented modeling of smart grid agents
- Each “module” runs as a separate computing process
- Event-driven, distributed simulation
- Communication by TCP/IP



Simulation Sequence of Events

1. Inflexible Load simulates new values of load for each bus
2. New values of load are transmitted
3. Inflexible Load creates load forecast for each bus for the next 24hrs
4. Inflexible Load sends load forecast to Price Forecaster



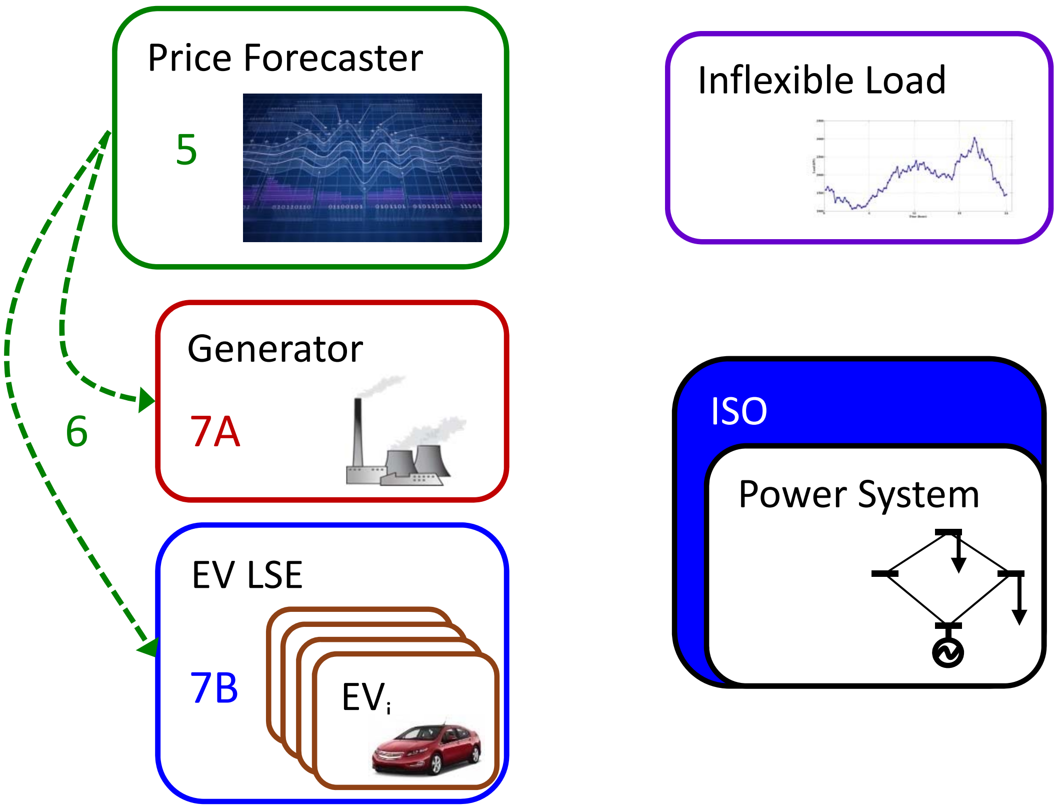
Carnegie Mellon

Simulation Sequence of Events

5. Price Forecaster creates a price forecast for each bus for the next 24 hrs

6. Price forecasts are sent to Generators and EV LSEs

7. In Parallel
   A. All Generators create supply bid functions
   B. All EV LSEs create aggregate demand bid functions



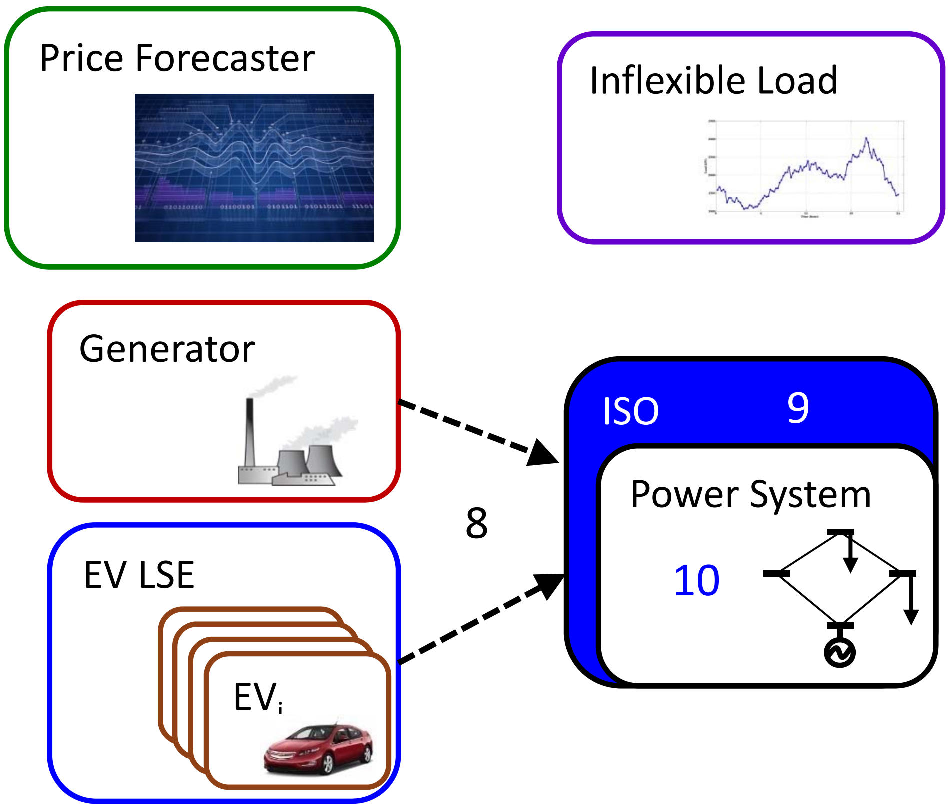
Carnegie Mellon

Simulation Sequence of Events

8. Demand and supply bids are submitted to the ISO

9. ISO updates power system object with new data

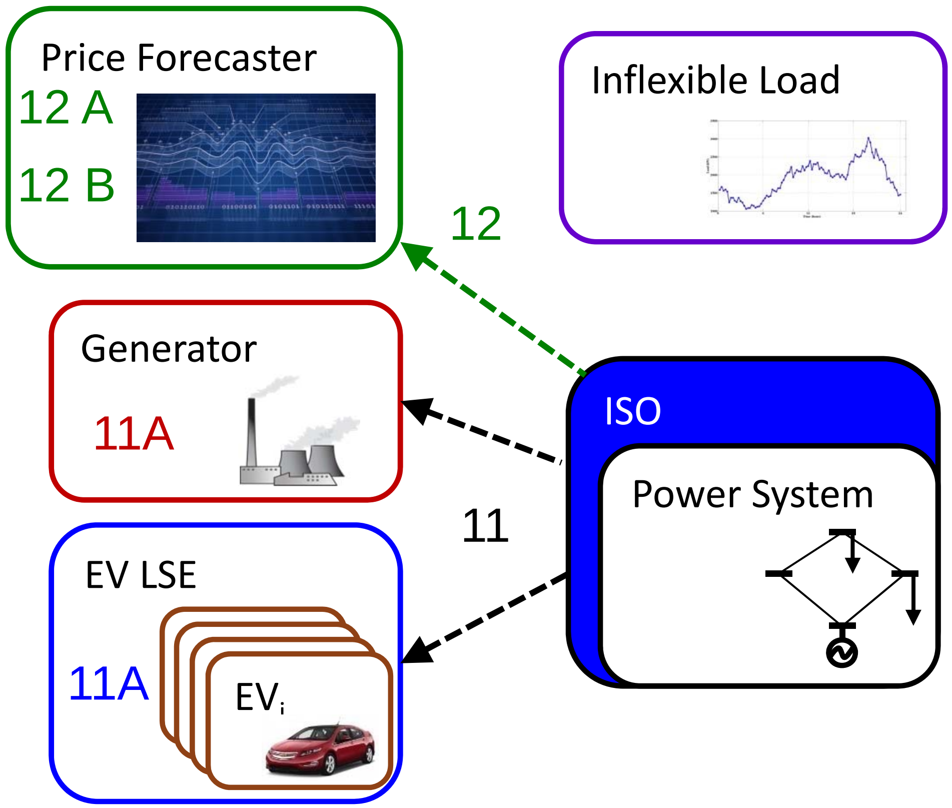
10. Power System object performs DCOPF to clear power market



Simulation Sequence of Events

11. ISO sends market clearing prices and quantities to market participants
    A. Market participants advance internal clocks

12. ISO sends market clearing price and quantity data to the Price Forecaster
    A. Price Forecaster may update price model using new data
    B. Price Forecaster advances internal clock

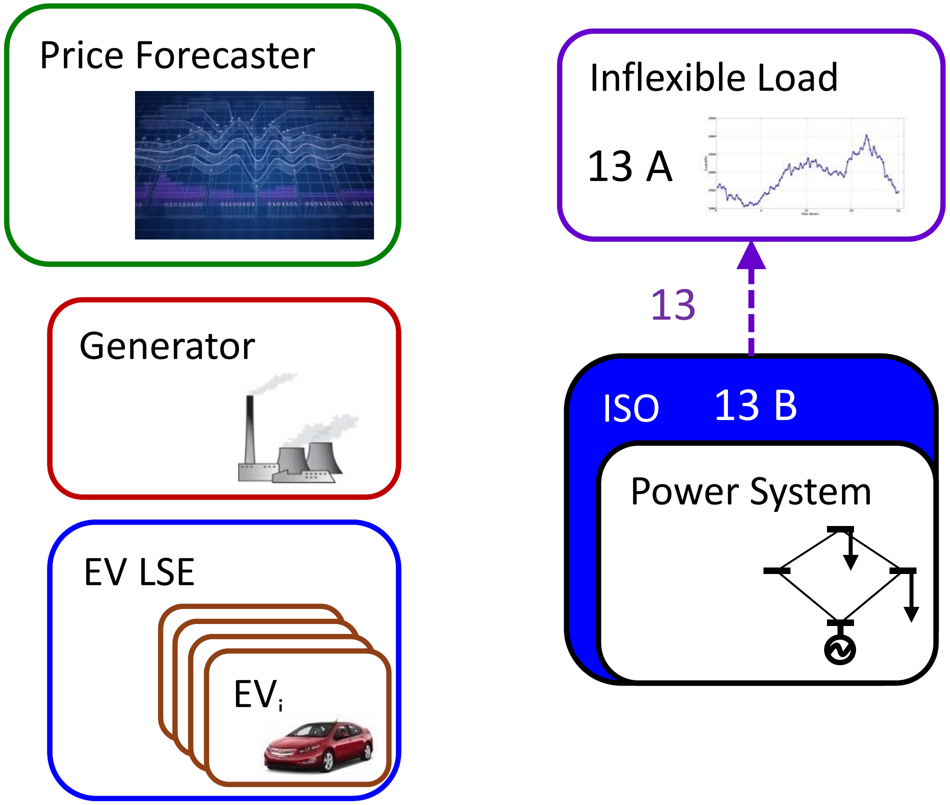


Simulation Sequence of Events

13. ISO notifies Inflexible Load that market has cleared
    A. Inflexible Load advances internal clock
    B. ISO advances internal clock

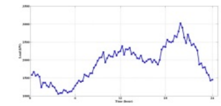
14. Sequence Repeats

*Simulation runs on 10 minute timesteps

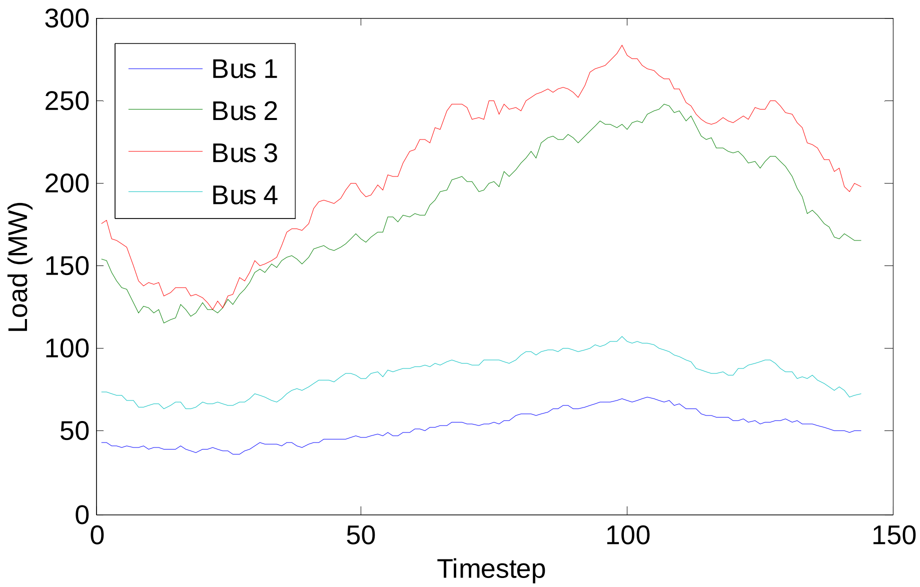


Inflexible Load Module

Inflexible Load



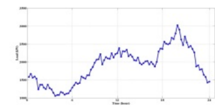
- Important functions
  - Randomly generates new load values for all buses
  - Forecasts load for all buses
- Bus loads modeled as cross-correlated stochastic processes
- Model fit to DUQ node (Pittsburgh) load data



Carnegie Mellon

Inflexible Load Module

Inflexible Load



- Mean + SARMA time series model

$$\hat{L}_j[t] = s_j \mu[t] + x_j[t]$$

- μ - Mean model
  - Accounts for Time of Day, Workday/Weekend seasonality

$$\mu[t] = \beta_0 + \beta_w I_w[t] + \sum_{i=2}^{24} \beta_i I_i[t] + \sum_{i=2}^{24} \beta_{w,i} I_i[t] I_w[t]$$

- x - Seasonal ARMA model

$$x_j[t] = \phi_1 x_j[t-1] + \phi_{24} x_j[t - 24\frac{1}{\Delta t}] + \phi_{24*} x_j[t - 24\frac{1}{\Delta t} - 1]$$

- Cross-correlated noise

$$L[t] = diag(s)\mu[t] + x[t] + N(0, \Sigma)$$

Price Forecaster Module

Price Forecaster

- Important functions
  - Stores market results
  - Fits model of prices using stored market data
  - Forecasts prices for next 24 hours, at all buses
- Mean + AR model of prices for each bus *j*

$$\hat{\pi}_j[t] = \mu_j[t] + x_j[t]$$

- Mean model

$$\mu_j[t] = \beta_{j,0} + \beta_{j,w} I_w[t] + \sum_{i=2}^{144} \beta_{j,i} I_i[t] + \sum_{i=2}^{144} \beta_{j,w,i} I_i[t] I_w[t] + \beta_{j,L,1} \hat{L}[t] + \beta_{j,L,2} \hat{L}^2[t]$$

- AR model

$$x_j[t] = \phi_1 x_j[t-1]$$

Generator Module

Generator

❖ Important functions

- Create supply function for market
- Calculate dispatch Pmin and Pmax using current state

❖ Generator's Profit Maximization Problem [1,2]

$$\max_{P[t]} \sum_{t=1}^{T} \hat{\pi}[t]P[t] - C\left(P[t]\right)$$

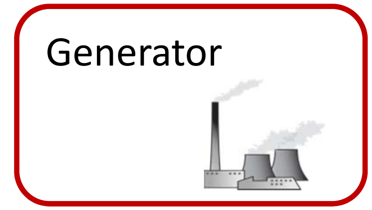
Subject to:

$$|P[t] - P[t-1]| \leq R, \quad \forall t$$

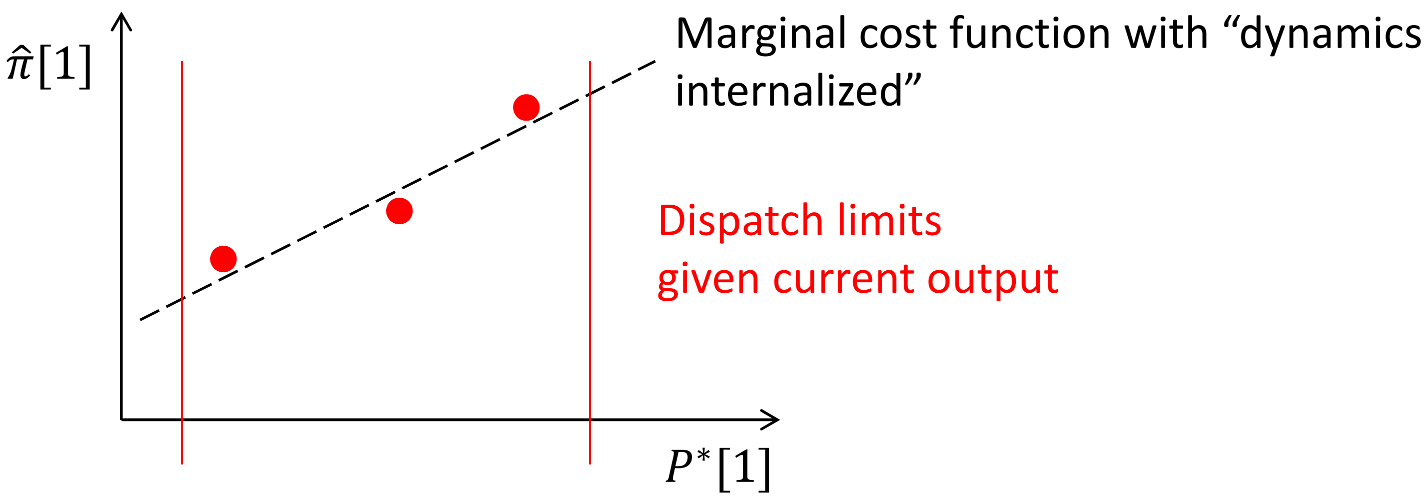
$$P_{min} \leq P[t] \leq P_{max}, \quad \forall t$$

Carnegie Mellon

Generator Module



- Creation of Supply Function [1,2]
  - Solve 3 optimization problems
    - $\hat{\pi}$
    - $\{1.1 * \hat{\pi}[1], \hat{\pi}[2], \ldots, \hat{\pi}[T]\}$
    - $\{0.9 * \hat{\pi}[1], \hat{\pi}[2], \ldots, \hat{\pi}[T]\}$

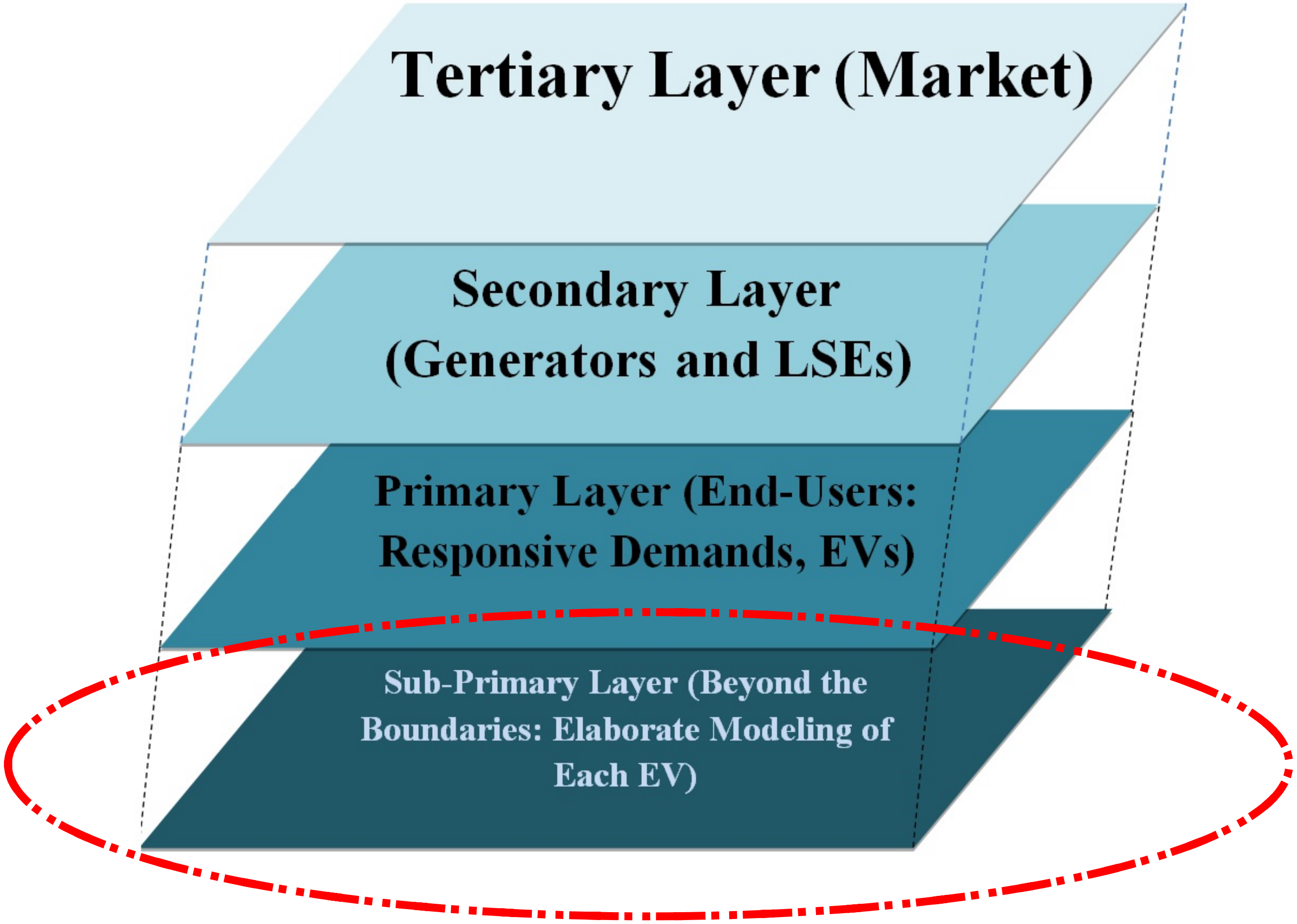


EV Driving Simulation Object

- Important functions
  - Randomly generates transportation behavior
  - Determines energy needs and charging deadline for each EV

- Generating transportation behavior
  - Generated trip depends on Time of Day, Weekend/Workday
  - Each time an EV plugs-in:
    - Randomly generate next unplug time
    - Randomly generate following plug-in time
    - Determine state of charge required to complete the trip

EV Modeling Based on Drivers Behavior



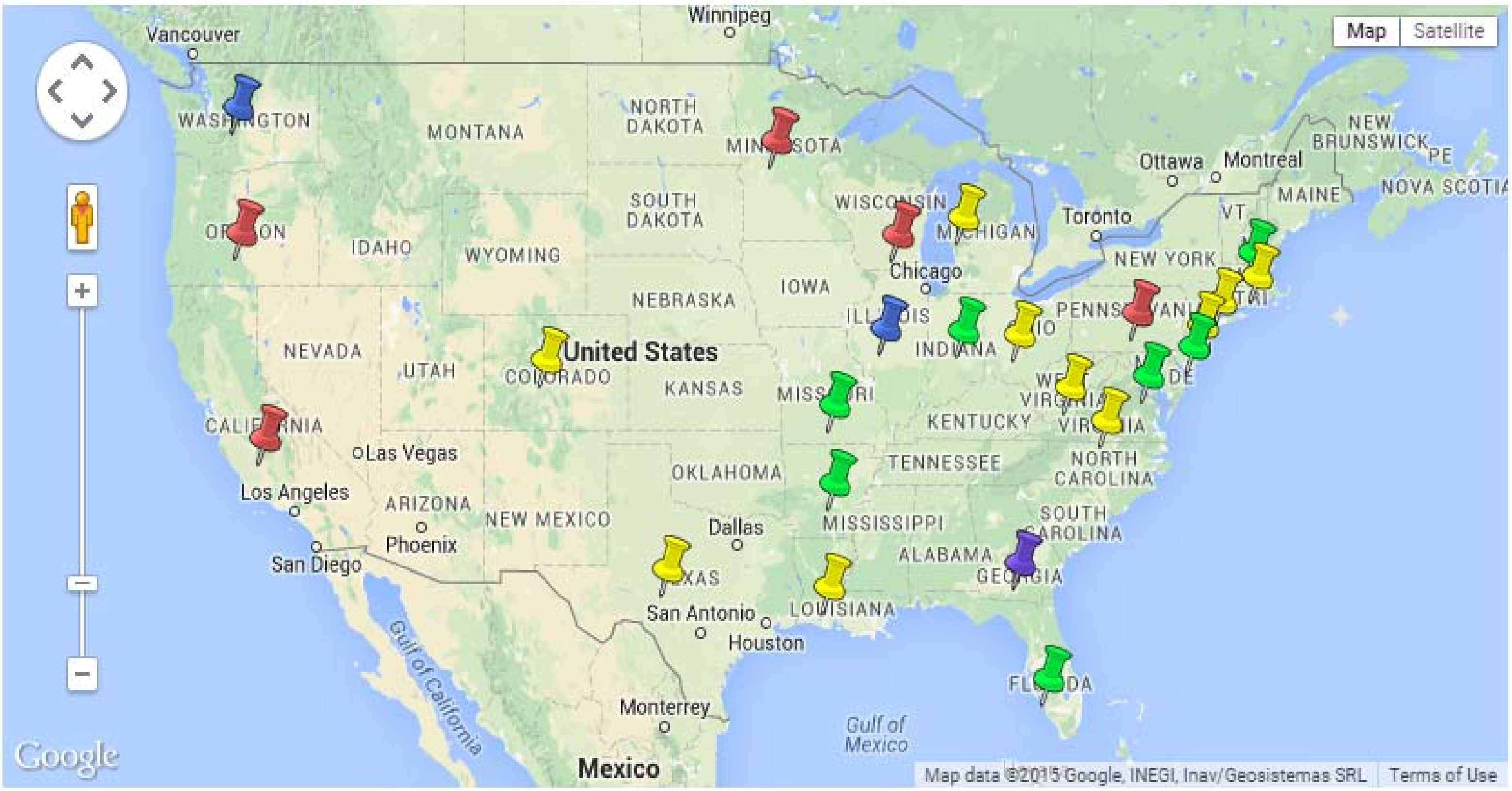
Questions and Objective

Let's assume that you want to drive from point A to point B on a map:

- Does vehicle powertrain technology matter for the energy consumption rate?
- There are many *types of vehicle* and *driving behaviors*…

How to determine *energy consumption* for each vehicle type based on the available driving cycle and the technical features of vehicle?

EV Drivers Behavior Data Set



1 to 50 miles collected | 51 to 250 miles collected | 251 to 500 miles collected | 501 to 800 miles collected | 801 to 14356 miles collected

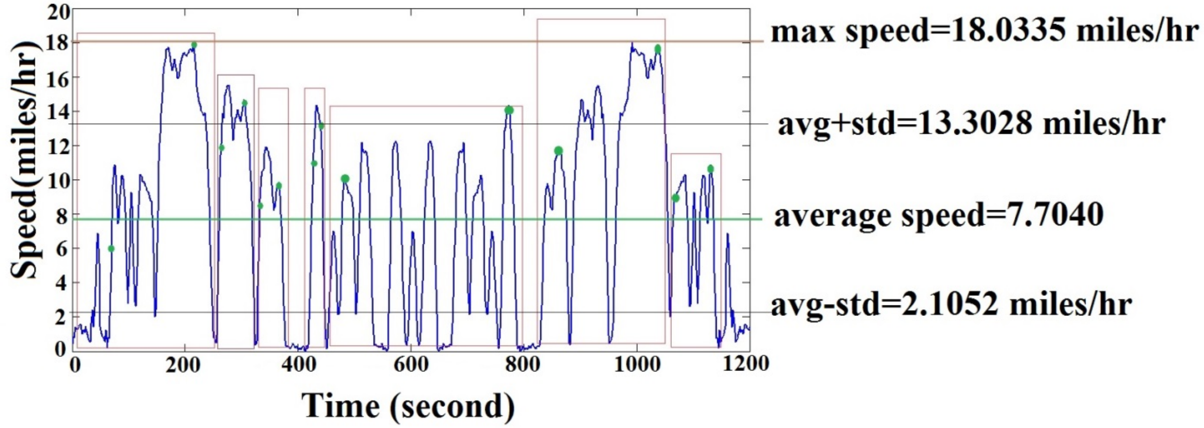
Source:http://chargecar.org/data

EESG

Carnegie Mellon

EV Energy Needs

- Sample driving cycle for one vehicle

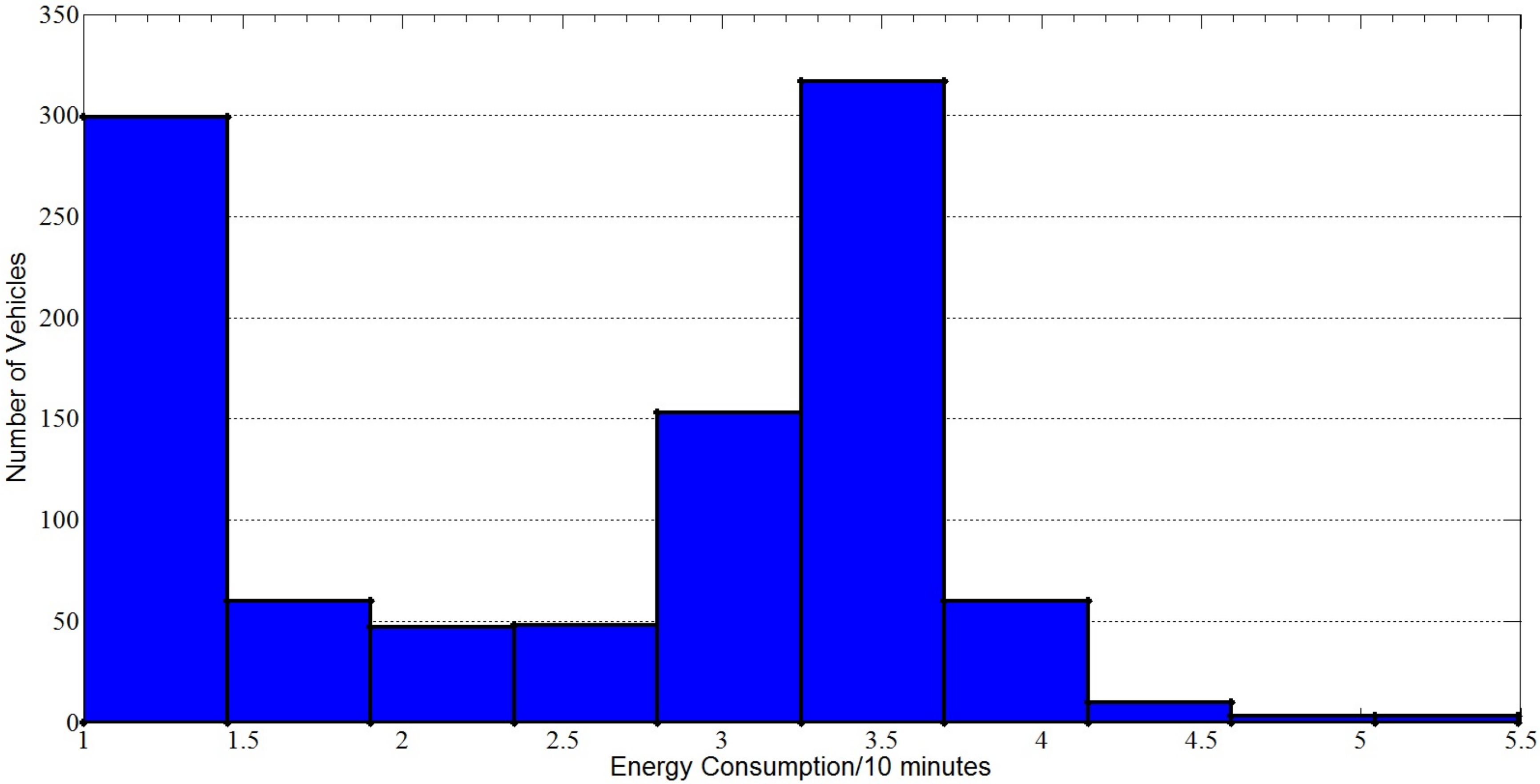


- Power Consumption Calculation

$$P_v = \frac{1}{2}\frac{M_v}{t_a}(v_b^2 + v_f^2) + \frac{1}{2}\rho C_d A_v v_f^3 + C_r M_v g v_f$$

- Calculated for many vehicle types and driving cycles

Distribution of Energy Consumption/10 minutes



EV Object

- Important functions
  - Requests new driving schedule from Driving Simulation
  - Updates own state of charge and connection status
  - Optimize charging given driving schedule, prices
  - Calculates own dispatch Pmin/Pmax
- EV's Charge Optimization Problem

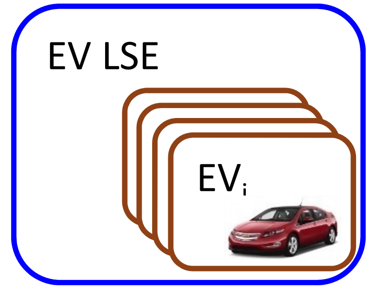
$$\min_{P[t]} \sum_{t=1}^{T-1} \hat{\pi}[t] P[t] \Delta_t$$

Subject to:

$$1) \quad E_{req} \leq \sum_{t=1}^{T-1} \eta \Delta_t P[\mathrm{t}] + E_0$$

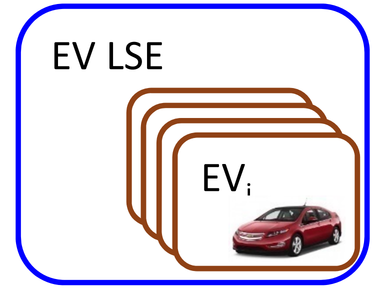
$$2) \quad 0 \leq P[t] \leq P_{max}, \quad \forall t \in \{1, \ldots, T-1\}$$

EV LSE Module

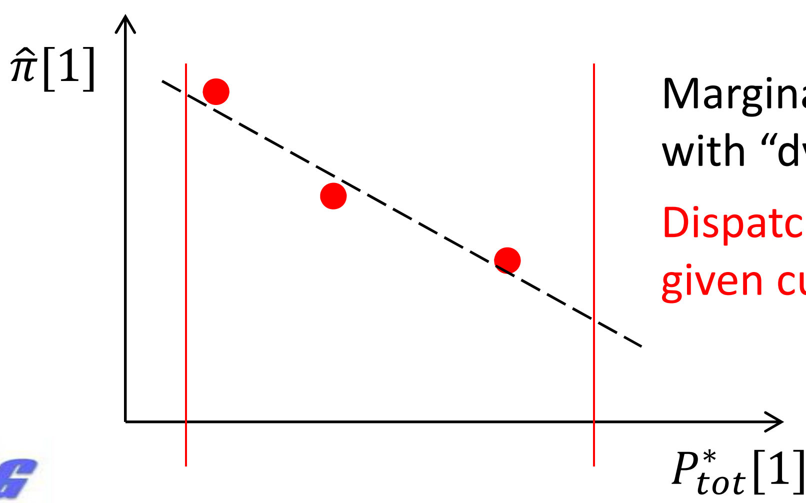


- Important functions
  - Relays price forecast to EVs
  - Requests demand points from EVs
  - Creates Aggregate EV demand function
  - Calculates aggregate dispatch Pmin and Pmax of EVs
  - Dispatches EVs

EV LSE Module



- Creation of aggregate demand function [3]
  - Submits 3 forecasts to each EV
    - $f_1 = \hat{\pi}$
    - $f_2 = \{1.1 * \hat{\pi}[1], \hat{\pi}[2], \dots, \hat{\pi}[T]\}$
    - $f_3 = \{0.9 * \hat{\pi}[1], \hat{\pi}[2], \dots, \hat{\pi}[T]\}$
  - Estimates aggregate demand function

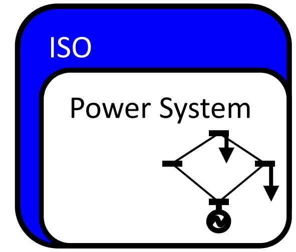


Marginal benefit function with “dynamics internalized”

Dispatch limits given current states

Carnegie Mellon

Independent System Operator (ISO)



- ISO important functions
  - Updates Power System object with new demand and supply bids
  - Communicates market clearing prices, quantities to other modules
- Power System important functions
  - Solves DCOPF with flexible generation and demand

$$\min_{P_i, D_i} \sum_i C_i(P_i) - \sum_i B_i(D_i)$$

Subject to:

1) $\sum_i P_i = \sum_i D_i$

2) $|F_l| \leq F_l^{\max} \quad \forall l$

3) $P_i^{min} \leq P_i \leq P_i^{max} \quad \forall i$

4) $D_i^{min} \leq D_i \leq D_i^{max} \quad \forall i$

Demo

- Simple 4 bus power system
- 500 MW mean system load
- 1 generator
- 500 EVs ~14% of mean load

References

1. Marija Ilic, Le Xie, and Jhi-Young Joo, "Efficient coordination of wind power and price-responsive demand—Part I: Theoretical foundations." *Power Systems, IEEE Transactions on* , 2011.

2. Marija Ilic, Le Xie, and Jhi-Young Joo, "Efficient coordination of wind power and price-responsive demand—part ii: Case studies." *Power Systems, IEEE Transactions on*, 2011.

3. Jhi-Young Joo. "Adaptive Load Management: Multi-Layered And Multi-Temporal Optimization Of The Demand Side In Electric Energy Systems." *PhD Thesis*, Carnegie Mellon University, 2013.