CPS: Synergy: Architectural and Algorithmic Solutions for Large Scale PEV Integration into Power Grids

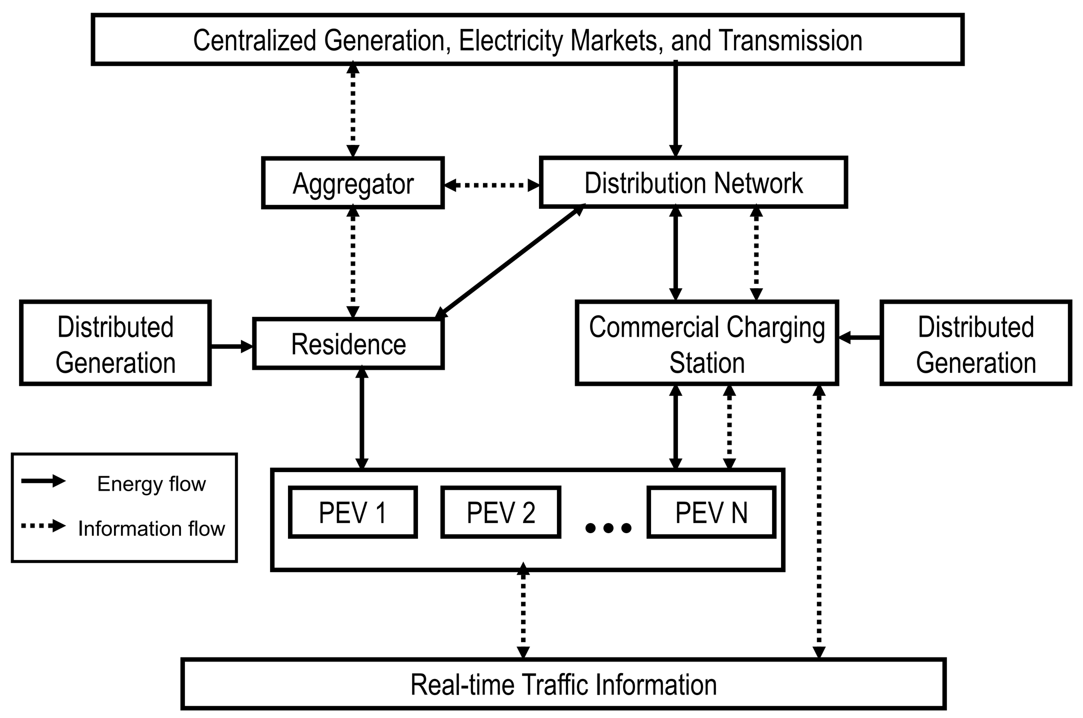
D. Kirschen and M. Ortega-Vazquez
University of Washington

P. Bauer, Y.-F. Huang, V. Gupta
University of Notre Dame

U. Topcu
University of Texas at Austin

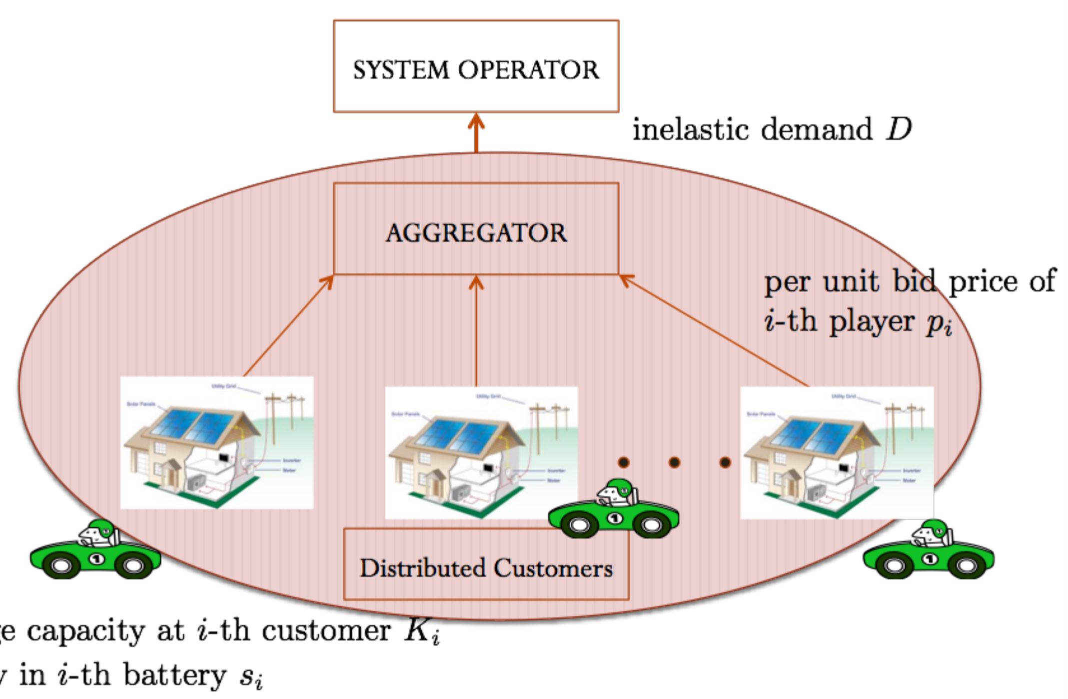
Project Objectives

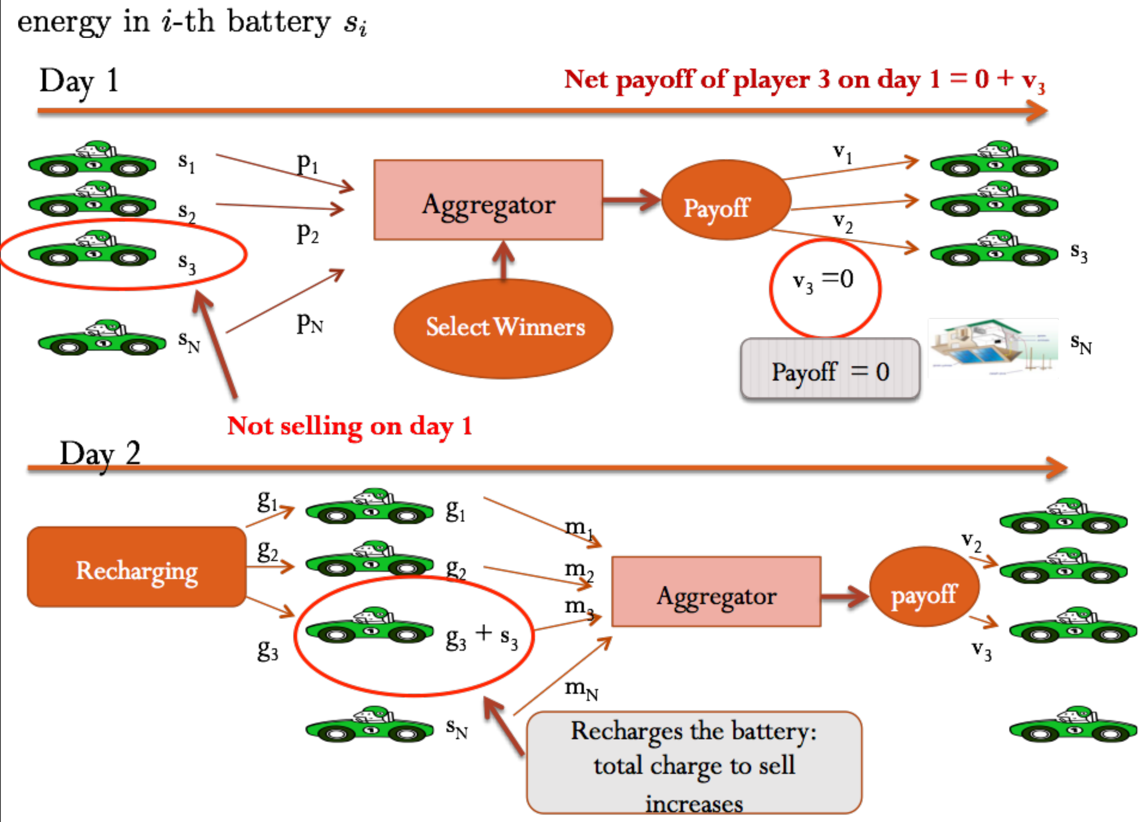
What will be the effect on power grid of large scale PEV integration?



Provision of Energy to the Grid

Mitigation of distribution overloads via customers selling energy to aggregator when both maximize profits in **repeated coupled** markets.





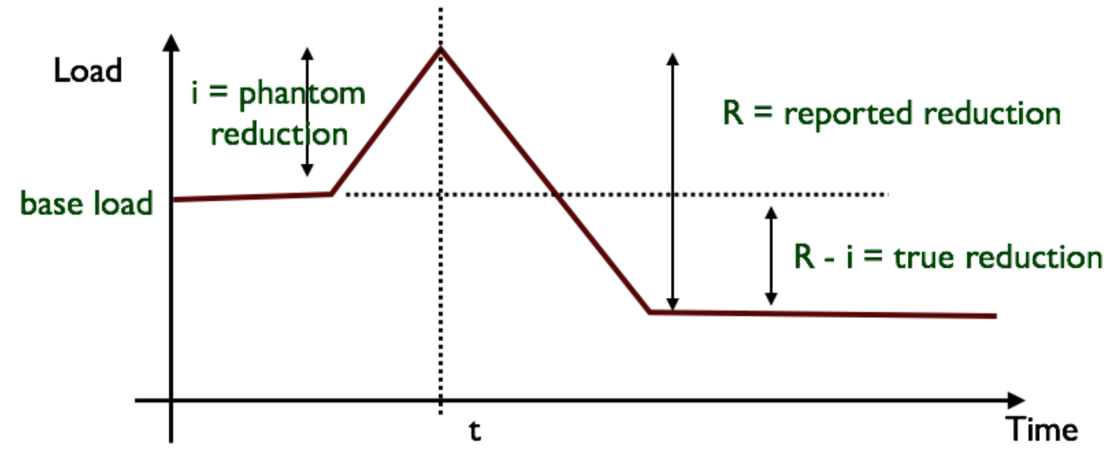
A strategy combination of the form $\pi_i(s) = \tilde{p}_i(s, \pi)$ for all states s is a Markov Perfect Equilibrium

$$\tilde{p}(s,\pi)s + \beta \sum_{s' \in S} V_i^{\pi}(s') f\left(s'; (0, \pi_{-i}(s)), s\right)$$

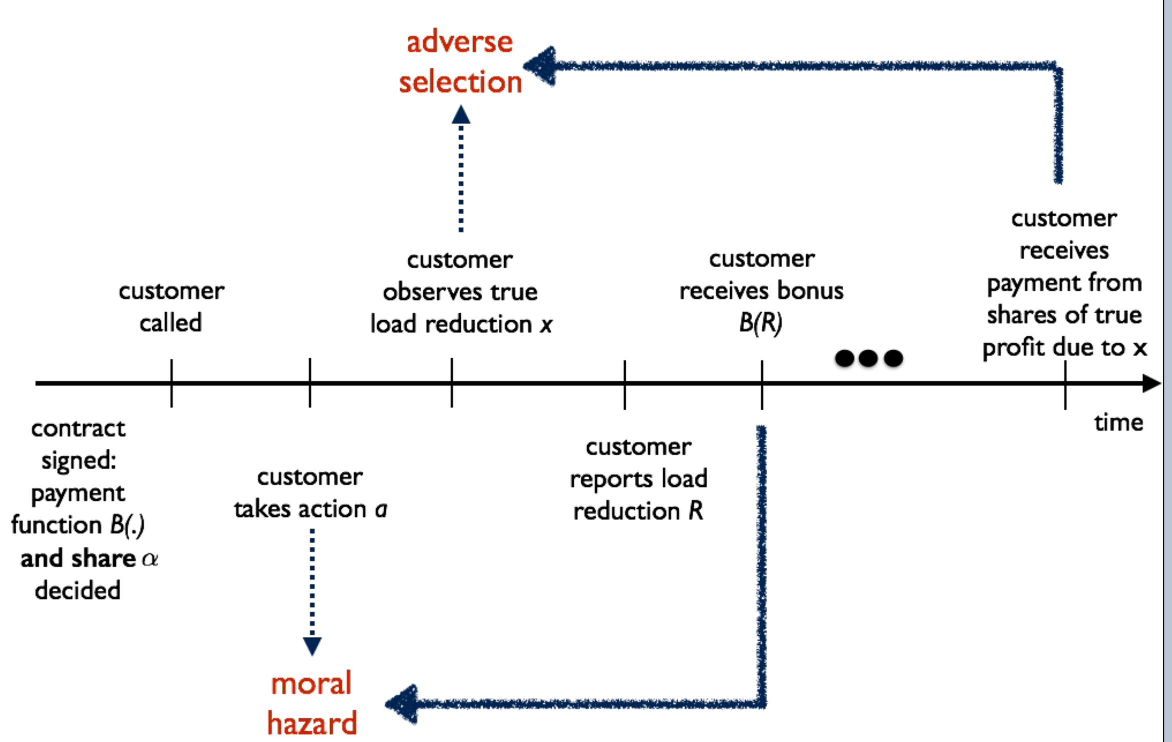
$$= \beta \sum_{s' \in S} V_i^{\pi}(s') f\left(s'; (c^{\star}, \pi_{-i}(s)), s\right)$$

Phantom Demand Response

EVs can provide demand response services to the grid. How should they be compensated?



Possible even with constant monitoring



$$\max_{\alpha, B(.), R} E[U_{com}] = E[(1-\alpha)x - B(R)]$$

$$W = \alpha x - g(R - x) + B(R)$$

subject to

- optimal choice of action a by the customer

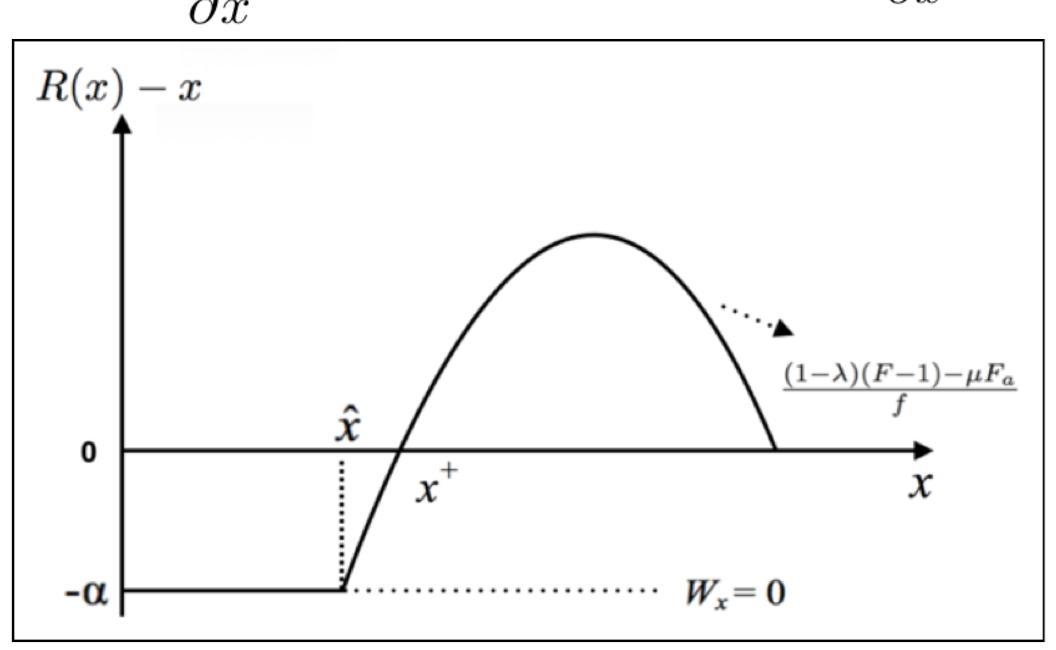
$$\frac{\partial E[U_{cus}]}{\partial a} = 0 \qquad \frac{\partial^2 E[U_{cus}]}{\partial a^2} \le 0$$

- individual rationality

$$E[U_{cus}] \ge 0 \qquad W \ge 0$$

- incentive compatibility

$$\frac{\partial R}{\partial x} \ge 0 \qquad W_x = \alpha + \frac{\partial g(R-x)}{\partial x}$$

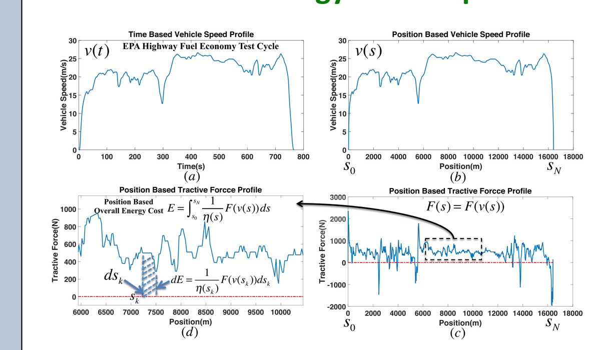


$$\frac{\partial U_{com}}{\partial \alpha} = E[R - x] \Rightarrow \text{Optimal value of } \alpha > 0$$

Eco Driving and Routing

Optimal Speed Profiles for Sustainable Driving

Position-Based Energy Consumption Model



Objective: Optimal Speed Profile v(s) with regard to location

Longitudinal Tire Force:

$$F(s) = F(v(s)) = F_{air}(s) + F_{ac}(s) + F_{hc}(s) + F_{rr}(s)$$

Position-Based Acceleration:

$$a(s) = \frac{d}{dt}\left(\frac{ds}{dt}\right) = \frac{dv(s)}{dt} = \frac{dv(s)}{ds}\frac{ds}{dt} = \frac{dv(s)}{ds}v(s)$$

Position-Based Energy Cost:

$$E = \int_{s_0}^{s_N} dE = \int_{s_0}^{s_N} \frac{1}{\eta(s)} F(s)ds = \int_{s_0}^{s_N} \frac{1}{\eta(s)} F(v(s))ds$$

Minimum Energy Cost with Time Constraint

Infinite dimensional Model

$$\min_{v(s)} \int_{s_0}^{s_N} \frac{1}{\eta(s)} F(v(s))ds \quad \text{subject to} \quad v_{ll}(s) \le v(s) \le v_{lu}(s), \quad \int_{s_0}^{s_N} \frac{1}{v(s)} ds \le t_0$$

Discretized Convex Model

$$\min_{\vec{v}} E(\vec{v}) \quad \text{subject to} \quad v_{ll}^i \le v_i \le v_{lu}^i \quad i = 0,1,...,N, \quad T(\vec{v}) \le t_0$$

Robust Optimization Model

$$\min \max_{w_l^i \le w_i \le w_u^i} E(\vec{v}, \vec{w}) \quad \text{subject to} \quad v_{ll}^i \le v_i \le v_{lu}^i \quad i = 0,1,...,N, \quad T(\vec{v}) \le t_0$$

Minimum Time Cost with Energy Constraint

Infinite dimensional Model

$$\min_{v(s)} \int_{s_0}^{s_N} \frac{1}{v(s)} ds \quad \text{subject to} \quad v_{ll}(s) \le v(s) \le v_{lu}(s), \quad \int_{s_0}^{s_N} \frac{1}{\eta(s)} F(v(s))ds \le E_0$$

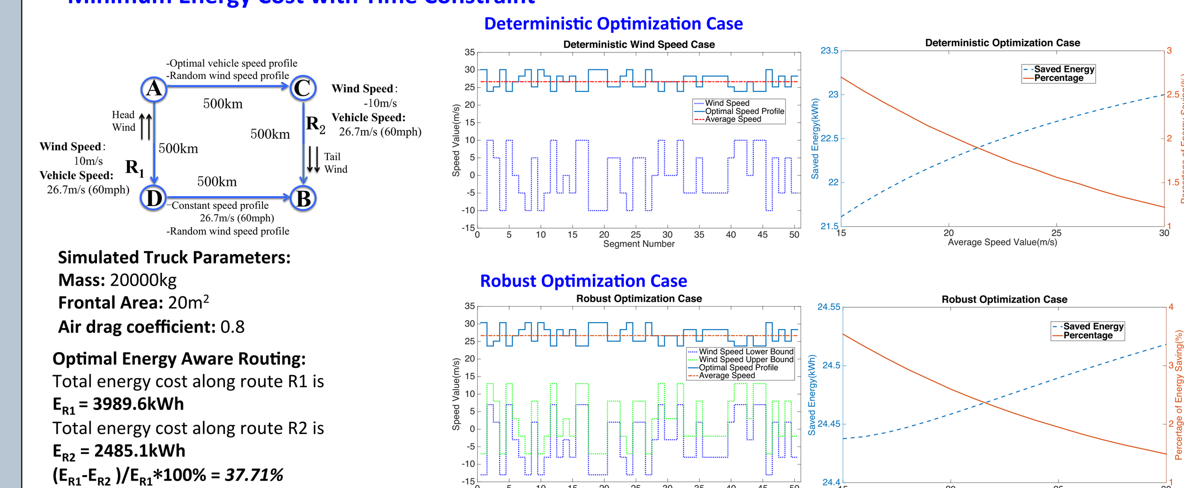
Discretized Convex Model

$$\min_{\vec{v}} T(\vec{v}) \quad \text{subject to} \quad v_{ll}^i \le v_i \le v_{lu}^i \quad i = 0,1,...,N, \quad E(\vec{v}) \le E_0$$

Robust Optimization Model

$$\min_{\vec{v}} T(\vec{v}, \vec{w}) = T(\vec{v}) \quad \text{subject to} \quad v_{ll}^i \le v_i \le v_{lu}^i, \quad i = 0,1,...,N; \quad w_l^i \le w_i \le w_u^i, \quad i = 0,1,...,N; \quad E(\vec{v}, \vec{w}) \le E_0$$

- **Minimum Energy Cost with Time Constraint**

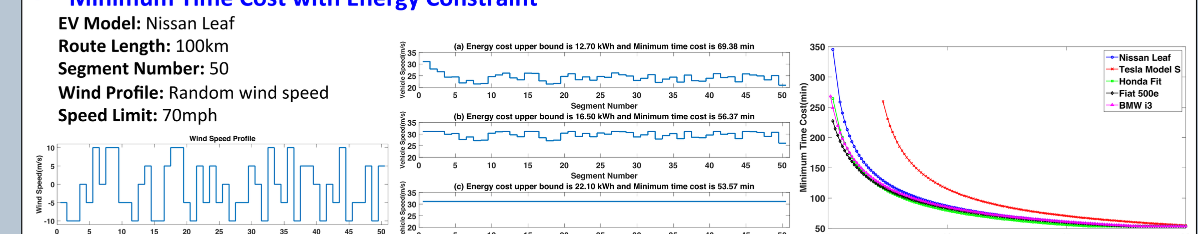


Simulated Truck Parameters:
Mass: 20000kg
Frontal Area: 20m^2
Air drag coefficient: 0.8

Optimal Energy Aware Routing:
Total energy cost along route R1 is
E_{R1} = 3989.6kWh
Total energy cost along route R2 is
E_{R2} = 2485.1kWh
$(E_{R1}-E_{R2})/E_{R1}$*100% = *37.71%*

- **Minimum Time Cost with Energy Constraint**

EV Model: Nissan Leaf
Route Length: 100km
Segment Number: 50
Wind Profile: Random wind speed
Speed Limit: 70mph



Optimal Stochastic Eco-Routing Solutions

Stochastic Eco-Routing Decision-Making Procedure

Stochastic Integer Programming

$$\min_{x_i} \mathbf{e_0}^T\mathbf{x} \quad \text{s.t.} \quad P_r\{\mathbf{e}^T\mathbf{x} \le \eta\} \ge p, \quad \mathbf{Nx} = \mathbf{b}, \quad \mathbf{N} \in Z^{n\times m}\ \mathbf{b} \in Z^n, \quad \mathbf{x} \in Z^m,\ x_i \in \{0,1\}$$

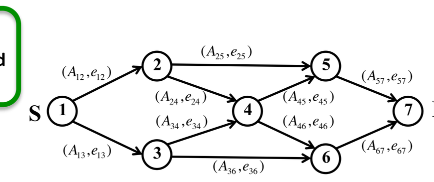
High-Efficient Solver
(1) Primal–Dual Interior Point Method
(2) Optimal Path Reconstruction

Stochastic Convex Programming

$$\min_{x_i} \mathbf{e_0}^T\mathbf{x} \quad \text{s.t.} \quad P_r\{\mathbf{e}^T\mathbf{x} \le \eta\} \ge p, \quad \mathbf{Nx} = \mathbf{b}, \quad \mathbf{N} \in Z^{n\times m}\ \mathbf{b} \in Z^n, \quad 0 \le x_i \le 1,\ x_i \in \mathbf{x} \in R^m$$

Second Order Cone Programming

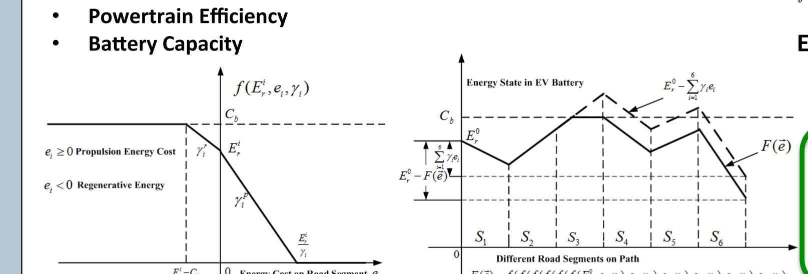
$$\min_{x_i} \mathbf{e_0}^T\mathbf{x} \quad \text{s.t} \quad \Phi^{-1}(p)\sqrt{\mathbf{x}^T\Sigma\mathbf{x}} + \sum_{i=1}^{m}\mu_i x_i - \eta \le 0, \quad \mathbf{Nx} = \mathbf{b}, \quad \mathbf{N} \in Z^{n\times m}\ \mathbf{b} \in Z^n, \quad 0 \le x_i \le 1,\ x_i \in \mathbf{x} \in R^m$$



Objective: Minimize the mean value of overall energy cost for the selected route

Considerations of Electric Drive Limits

- Powertrain Efficiency
- Battery Capacity



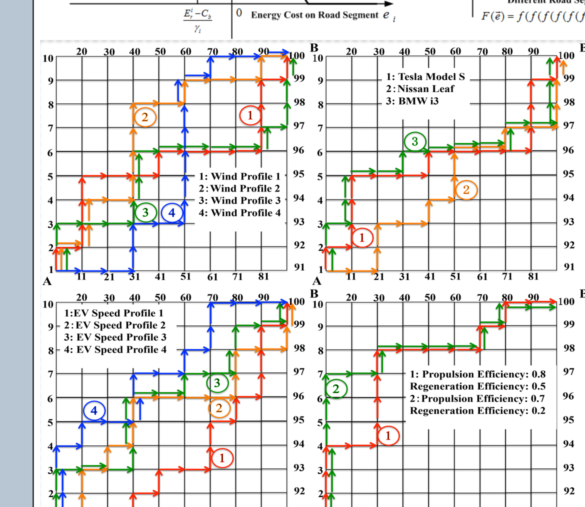
Energy Cost function

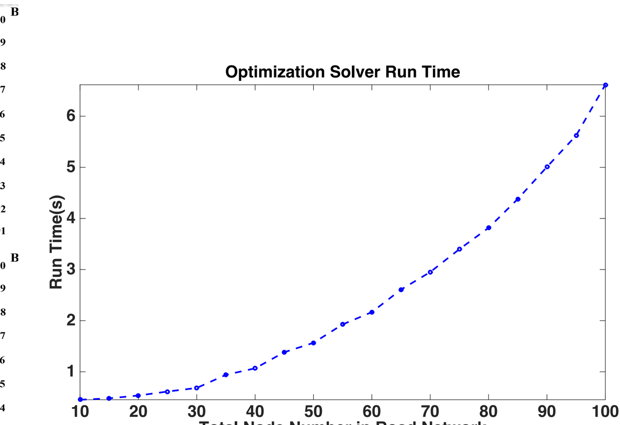
$$f(E_r^i, e_i, \gamma_i) = \begin{cases} C_b & \gamma_i e_i < E_r^i - C_b \\ E_r^i - \gamma_i e_i & E_r^i - C_b \le \gamma_i e_i \le E_r^i \\ 0 & \gamma_i e_i > E_r^i \end{cases}$$

Efficiency Model

$$\gamma_i = \begin{cases} \frac{1}{\gamma_i^p} & e_i \ge 0 \\ \gamma_i^r & e_i < 0 \end{cases}$$

$$\min_{\mathbf{x}} \sum_{i=1}^{m} \gamma_i e_0^i x_i \quad \text{s.t.} \quad P_r\{\sum_{i=1}^{m} \gamma_i e_i x_i \le \widetilde{E_0}\} \ge p, \quad \mathbf{Nx} = \mathbf{b} \quad x_i \in \{0,1\}, \mathbf{N} \in Z^{n\times m}, \mathbf{b} \in Z^n$$





Commercial Charging Stations

Motivation

Study dynamic pricing and energy management policy for EV charging stations with renewable energy integration and energy storage.

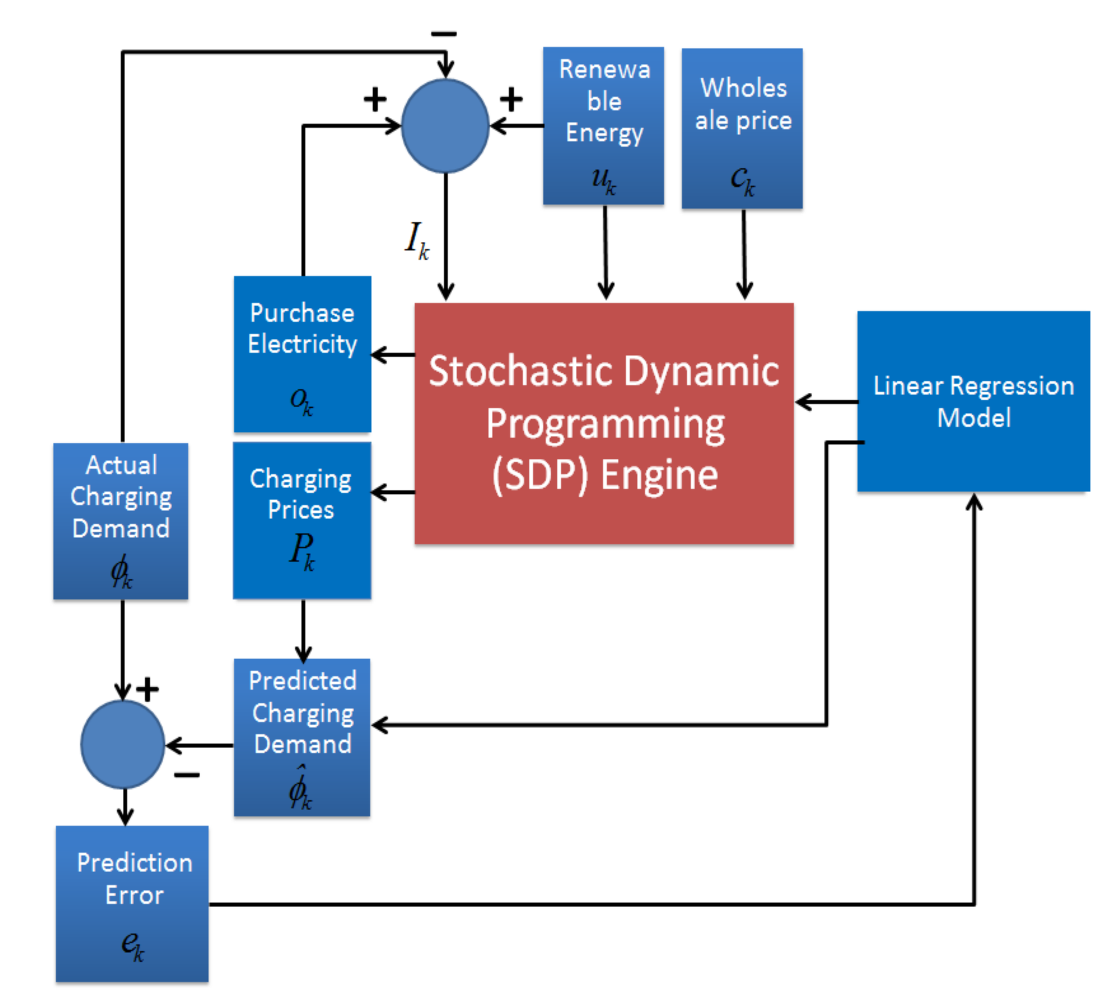
Methodology

❑ Multi objective programming (MOP): profitability, customer satisfaction, impact of EV charging on power grid.

$$\max\{E(\textstyle\prod_k)\} = \{E(W_k),\ E(G_k),\ E(-F_k)\},$$
$$\text{s.t.} \quad X_k \in U(X_k)$$

❑ Stochastic dynamic programming (SDP): Optimize the accumulated expected utility over multiple horizons recursively.

$$J_k(I_k, u_k) = \max_{X_k \in U_k(X_k)} E\{\textstyle\prod_k + J_{k+1}(I_{k+1}, u_{k+1})\}$$
$$= \max_{X_k \in U_k(X_k)} \{E(\textstyle\prod_k(I_k, u_k)) + E_{u_{k+1}}(J_{k+1}(I_{k+1}, u_{k+1}))\}.$$



Input: c_k
Output: P_k, o_k
System state: I_k, u_k

Results

❑ SDP algorithm reaches up to 8% profit gain compared to greedy algorithm.

❑ Pricing signals can reshape tempo-spatial charging demand to reduce stress on power grid.

❑ A low-cost energy system can enhance profitability and protect customer from wholesale electricity fluctuation.