FORCES
FOUNDATIONS OF RESILIENT CYBER-PHYSICAL SYSTEMS

Responsive Load Control

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Motivation

- The electrical power drawn by plug-in electric vehicle (PEV) chargers will (eventually?) begin to impact the grid.
- At the system-wide level, control objectives tend to focus on filling the overnight valley in background demand.
- At the distribution level, proposed control strategies address:
  - Transformer overloads
  - Loss minimization
  - Voltage degradation
  - Tap-change minimization
- Few control strategies also take into account the effects of charging on battery health.

Goals

- A decentralized approach to scheduling PEV charging that considers trade-offs between:
  - Energy price
  - Battery degradation
  - Distribution network effects
- The resulting collection of PEV charging strategies should be efficient (socially optimal).
- Convergence should only require a few iterations.

Formulation

- PEV population: $\mathcal{N} \equiv \{1, ..., N\}$.
- Horizon: $\mathcal{T} \equiv \{0, ..., T-1\}$.
- Admissible charging strategies:

$$u_{nt} \geq 0, \quad t \in \mathcal{T}$$

$$\|\boldsymbol{u}_n\|_1 \equiv \sum_{t \in \mathcal{T}} u_{nt} \leq \Gamma_n$$

  where Γ_n is the energy capacity of the n-th PEV.
- The set of admissible charging controls is denoted $\mathcal{U}_n$.

Demand charge

- Distribution-level impacts are largely a consequence of coincident high charger power demand u_{nt}.
- Undesirable effects can be minimized by encouraging lower power levels,

$$Cost_{demand,nt} = g_{demand,nt}(u_{nt})$$

where $g_{demand,nt}(\cdot)$ is a strictly increasing function.

Battery degradation cost

Experimentation with LiFePO$_4$ lithium-ion batteries gave a degradation model:

$$\mathfrak{d}_{cell}(I, V) = \beta_1 + \beta_2 I + \beta_3 V + \beta_4 I^2 + \beta_5 V^2 + \beta_6 IV + \beta_7 V^3$$

relating energy capacity loss per second (in Amp$\times$Hour$\times$Sec^{-1}) to charging current I and voltage V.

- Degradation cost:

$$\mathfrak{g}_{cell}(I, V) = P_{cell} \Delta T V \mathfrak{d}_{cell}(I, V)$$

  where P_{cell} is the price (\$/Wh) of battery cell capacity.
- Over the useable state of charge (SoC) range, $V \approx V_{nom}$.
- Battery degradation cost can be expressed as:

$$\begin{aligned} Cost_{degrad,nt} &= g_{cell,n}(u_{nt}) = M_n \mathfrak{g}_{cell}\left(\frac{10^3 u_{nt}}{M_n V_{nom}}, V_{nom}\right) \\ &= a_n u_{nt}^2 + b_n u_{nt} + c_n \end{aligned}$$

Centralized formulation

System cost:

$$J(\boldsymbol{u}) \triangleq \sum_{t\in\mathcal{T}} \left\{ c\left(d_t + \sum_{n\in\mathcal{N}} u_{nt}\right) + \sum_{n\in\mathcal{N}} g_{nt}(u_{nt}) \right\} - \sum_{n\in\mathcal{N}} \left\{ h_n\left(\|\boldsymbol{u}_n\|_1\right) \right\}$$

where:

- $\boldsymbol{u}_n \in \mathcal{U}_n$ for all $n \in \mathcal{N}$.
- $c(\cdot)$ gives the generation cost with respect to the total demand $d_t + \sum_{n\in\mathcal{N}} u_{nt}$, and d_t denotes the aggregate inelastic base demand at time t.
- $g_{nt}(u_{nt}) = g_{demand,nt}(u_{nt}) + g_{cell,n}(u_{nt})$ captures the demand charge and battery degradation cost of the n-th PEV.
- $h_n\left(\|\boldsymbol{u}_n\|_1\right)$ denotes the benefit function of the n-th PEV with respect to the total energy delivered over the charging horizon, with:

$$h_n\left(\|\boldsymbol{u}_n\|_1\right) = -\delta_n\left(\|\boldsymbol{u}_n\|_1 - \Gamma_n\right)^2$$

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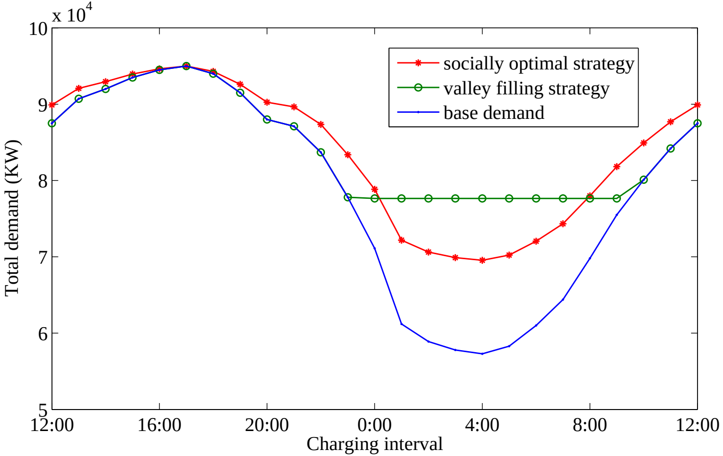
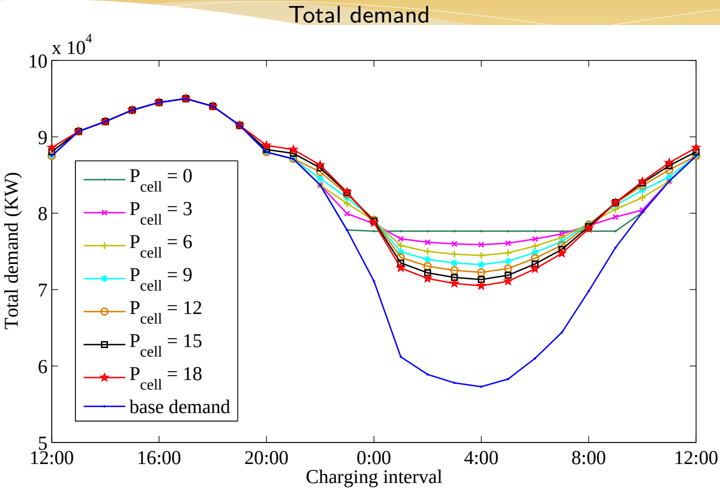
Example

Total demand



Example - varying P_{cell}



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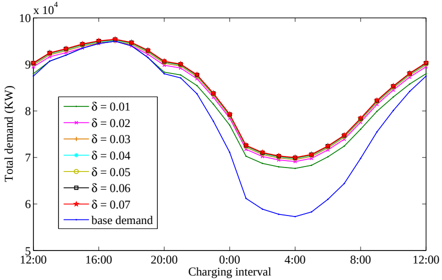
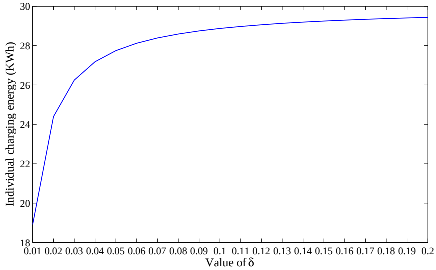
Example - varying terminal penalty, δ_n

Total demand



Delivered energy



Decentralized charging coordination

(S1) Each PEV autonomously determines its optimal charging strategy with respect to a given electricity price profile $\boldsymbol{p} \equiv (p_t, t \in \mathcal{T})$. This optimal strategy takes into account the trade-off between the electricity cost and local (demand and battery degradation) costs over the entire charging horizon.

(S2) The electricity price profile $\boldsymbol{p}$ is updated to reflect the latest charging strategies determined by the PEV population in (S1).

(S3) Steps (S1) and (S2) are repeated until the change in the price profile at (S2) is negligible.

Using an appropriate individual cost function and price update mechanism, (S1)-(S3) is convergent and achieves the socially optimal (centralized) solution.

Individual cost function

$$J_n(\boldsymbol{u}_n; \boldsymbol{p}) \triangleq \sum_{t \in \mathcal{T}} \left\{ p_t u_{nt} + g_{nt}(u_{nt}) \right\} - h_n\Big(\sum_{t \in \mathcal{T}} u_{nt} \Big)$$

- Cost is composed of energy cost, local (demand and battery degradation) cost, and the benefit derived from the total delivered energy.
- The optimal charging strategy of the n-th PEV, with respect to $\boldsymbol{p}$:

$$\boldsymbol{u}_n^*(\boldsymbol{p}) = \operatorname*{argmin}_{\boldsymbol{u}_n \in \mathcal{U}_n} J_n(\boldsymbol{u}_n; \boldsymbol{p})$$

- This optimal response has the form:

$$u_{nt}(\boldsymbol{p}, A_n) = \max\left\{0, [g'_{nt}]^{-1}(A_n - p_t)\right\}, \quad t \in \mathcal{T}$$

for some A_n, where g'_{nt} is the derivative of g_{nt}, and $[g'_{nt}]^{-1}$ denotes the corresponding inverse function.

Price profile update mechanism

- Let

$$p_t^+(\boldsymbol{p}) = p_t + \eta\Big(c'\big(d_t + \sum_{n\in\mathcal{N}} u_{nt}^*(\boldsymbol{p})\big) - p_t\Big), \quad t \in \mathcal{T}$$

  where $\eta > 0$ is a fixed parameter, and $\boldsymbol{u}_n^*(\boldsymbol{p})$ is the optimal charging strategy for the n-th PEV with respect to $\boldsymbol{p}$.
- Assuming the terminal valuation function h_n is increasing and strictly concave:

$$\|\boldsymbol{u}_n^*(\boldsymbol{p}) - \boldsymbol{u}_n^*(\boldsymbol{\varrho})\|_1 \leq 2\nu\|\boldsymbol{p} - \boldsymbol{\varrho}\|_1$$

Theorem: The decentralized algorithm converges to the efficient (centralized) solution $\boldsymbol{u}^{**}$.

- The proof establishes that

$$\|\boldsymbol{p}^+ - \boldsymbol{\varrho}^+\|_1 < \|\boldsymbol{p} - \boldsymbol{\varrho}\|_1$$

  so the price update operator $\boldsymbol{p}^+(\boldsymbol{p})$ is a contraction map.

Illustration - convergence

Evolution of $\|\boldsymbol{p}^{(k)} - \boldsymbol{p}^{**}\|_1$ for various values of the price update parameter η.

- Convergence is guaranteed for $0 < \eta < 1.017$.

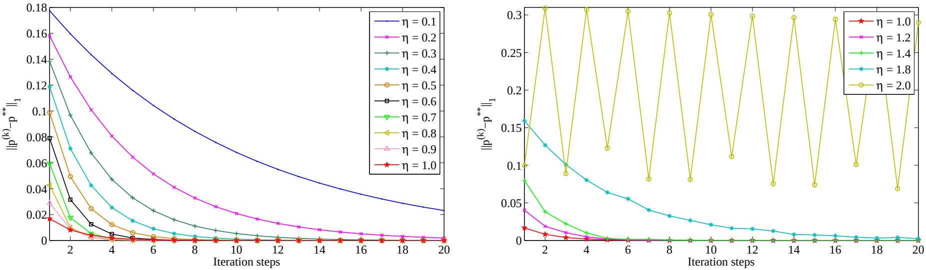


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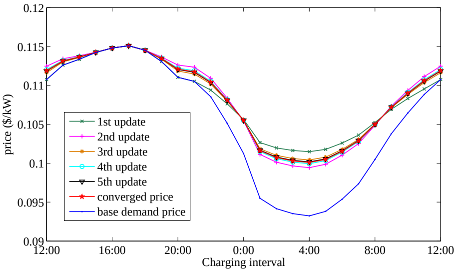
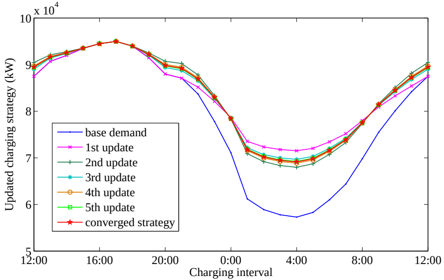
Illustration - algorithm updates

Price update parameter $\eta = 1$.

Price

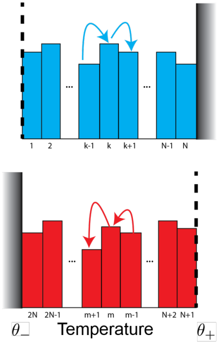


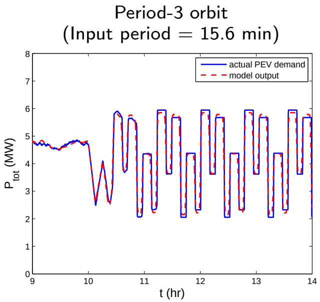
Total demand

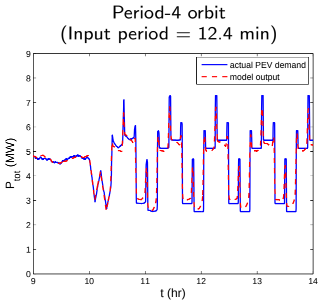


Ensemble control of hysteretic loads

- Example: thermostatically controlled loads.
- State-space modelling results in a nonlinear hybrid dynamical system.
  - Nonlinear because states and inputs multiple together.
  - Hybrid due to the influence of rapidly changing inputs.







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Conclusions

- Responsive load control offers an effective approach to compensating for the variability inherent in large-scale renewable generation and mitigating the effects of unplanned generation and transmission outages.
- Expansive communications networks and advances in distributed control algorithms facilitate precise, non-disruptive forms of load control.
- Numerous challenges remain though:
  - Highly distributed, heterogeneous, uncertain resources.
  - Control structure, nonlinearity, latency, inter-operability.
  - Data security.
  - Modelling and analysis.

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