Motivation
Problem Formulation
Our Results/Contribution
Numerical Results
Summary

Optimal Charging of Electric Vehicles in Smart Grid: Characterization and Valley-filling Algorithms

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- Motivation
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- Our Results/Contribution
 - Decomposition
 - Characterization of Optimal Solution
 - Algorithms
- **Numerical Results**









Motivation

- Increasing popularity of EV
 - Reduce CO₂
 - Reduce dependence of fossil fuel
- Possible Impact
 - ullet Uncoordinated charging + high penetration o grid overload
 - Coordinated charging is beneficial
 - Save infrastructure investment
 - Reduce operation cost
- Objective
 - Study optimal coordinated EV charging
 - Produce real time control algorithm under demand uncertainty











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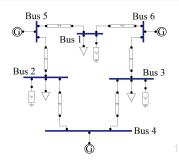






Optimal Power Flow Problem

- Objective
 - Generation cost
 - Power loss
- Constraints
 - Power constraints
 - Line constraints
 - Voltage constraints



- However, OPF only captures stable state
- Need to capture time-varying EV charging power



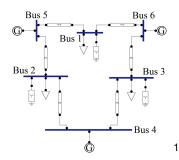




¹J. Lavaei and S. Low "Zero duality gap in optimal powers low problem" நட ஒடி

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Joint OPF-EV Charging Problem

- Consider two types of load
 - Price-inelastic load, e.g., lighting
 - Price-elastic load, e.g., EV
- Augment OPF with extra time dimension
- Add EV charging constraints
- Consider two different scenarios
 - Offline no uncertainty
 - Online uncertain future demand









System Model

- Vector of bus voltages $\mathbf{v}[t] = (V_1[t], \dots, V_n[t]) \in \mathbb{C}^n$
- Vector of current injection $\mathbf{i}[t] = (I_1[t], \dots, I_n[t]) \in \mathbb{C}^n$
- Let Y be the admittance matrix, by Kirchoff's Law

$$\mathbf{i}[t] = \mathbf{Y}\mathbf{v}[t]$$

Power injected at bus k

$$(\mathbf{p}[t]_k - \mathbf{p}[t]_k^d) + (\mathbf{q}[t]_k - \mathbf{q}[t]_k^d)j = V_k[t]I_k[t]^*$$

$$= (e_k^*\mathbf{v})(e_k^*\mathbf{i})^* = \operatorname{Tr}\{\mathbf{v}[t]\mathbf{v}[t]^*Y^*e_ke_k^*\}$$

• Introduce auxillary variable $W[t] = \mathbf{v}[t]\mathbf{v}[t]^*$







System Model

- Power Constraints
 - $P_k^{\min} \leq (\mathbf{p}[t])_k \leq P_k^{\max}$
 - $Q_k^{\min} \leq (\mathbf{q}[t])_k \leq Q_k^{\max}$
 - Trace $\{\mathbf{W}[t]\mathbf{Y}^*e_ke_k^*\}=$ $(\mathbf{p}[t])_k ((\tilde{\mathbf{p}}[t])_k + (\hat{\mathbf{p}}[t])_k) + ((\mathbf{q}[t])_k (\tilde{\mathbf{q}}[t])_k)_j$
- Voltage Constraints

•
$$(V_k^{\min})^2 \le \mathbf{W}[t]_{kk} \le (V_k^{\max})^2$$

- Line Constraints
 - $(\mathbf{W}[t]_{ll} \mathbf{W}[t]_{lm})\mathbf{Y}_{lm}^* \leq S_{lm}^{\max}$
- SDP constraints
 - $\mathbf{W}[t] \succeq 0$
 - rank(W[t]) = 1 (non-convex!)









System Model

- Objective is to minimize the sum of total generation cost and EV charging cost
- Joint OPF-EV Charging Problem can be written as

$$\min_{\{\mathbf{W}[t], \hat{\mathbf{p}}[t]\}} \sum_{t=1}^{T-1} \sum_{k \in \mathcal{N}} f_k((\mathbf{p}[t])_k) + \sum_{t=1}^{T-1} \sum_{k \in \mathcal{N}} \alpha_k(\hat{\mathbf{p}}[t])_k$$

such that all constraints (power, voltage, line, SDP) are satisfied







Assumptions

- State of the system is discrete
- OPF has zero duality gap→ rank relaxation is exact.
 - True for all distribution network [1]
 - [1] → zero gap for Joint OPF-EV charging [2]
- EV charging schedule is known
- EV charging cost is time-invariant







Joint OPF-EV Charging Problem

Challenges

- OPF is non-convex, so is the augmented problem
- Lots of control variables (with long time horizon)
- (Online case) Uncertain future demand

Approach

- Solve SDP relaxation of OPF exact for most network [1]
- Decompose
- Characterize optimal offline solution, follow the characterization online







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Decomposing Joint OPF-EV Charging Problem

- Decouple EV scheduling $(\tilde{\mathbf{p}}[t])$ from power dispatching (W[t])
- Define function

$$F(\hat{\mathbf{p}}[t] + \tilde{\mathbf{p}}[t]) = \min_{W[t]} \left(\sum_{k \in \mathcal{N}} f((\mathbf{p}[t]))_k \right)$$

s.t.all network constraints are satisfied







Decomposing Joint OPF-EV Charging Problem

Define nested optimization problem

$$\min_{\hat{\mathbf{p}}} \sum_{t=1}^{T-1} F(\tilde{\mathbf{p}}[t] + \hat{\mathbf{p}}[t]) + \alpha[t]^{\top} \hat{\mathbf{p}}[t]$$
s. t.
$$\sum_{t=1}^{T-1} \hat{\mathbf{p}}[t] = \mathbf{c}$$

$$\underline{\mathbf{r}}[t] \leq \hat{\mathbf{p}}[t] \leq \overline{\mathbf{r}}[t]$$

- Can we solve $\hat{\mathbf{p}}^*$ without knowing W^* ?
- ... Yes







Decomposing Joint OPF-EV Charging Problem

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- The nested optimzation problem has some nice structure
- (Theorem 1) $F : \mathbb{R}^N \to \mathbb{R}$ is convex
- Proof Sketch
 - F is a parameterized OPF problem
 - By zero duality gap, F look at the convex dual
 - $\tilde{\mathbf{p}}[t] + \hat{\mathbf{p}}[t]$ appears only in the dual objective function

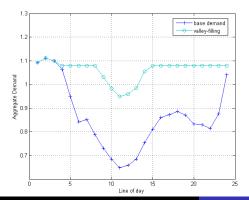






- (Theorem 2) Optimal EV charing profile is valley-filling
- We call a charging profile *valley-filling*, if there exists

$$\mathbf{a} \in \mathbb{R}^N$$
, such that $\hat{\mathbf{p}}[t] = [\mathbf{a} - \tilde{\mathbf{p}}[t]]_{\mathbf{r}}^{\mathbf{r}}$

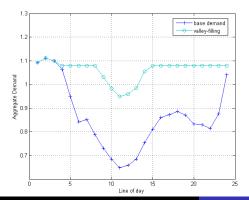






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Theorem 2 Proof Sketch

- Follow intuition of Jensen's inequality
- Use a swapping argument
 - If there exists an optimal non valley-filling profile
 - There are finite swapping steps to make the profile valley-filling
 - Each step will not increase the objective value









Valley-filling :
$$\hat{\mathbf{p}}[t] = [\mathbf{a} - \tilde{\mathbf{p}}[t]]^{\overline{\mathbf{r}}[t]}_{\underline{\mathbf{r}}[t]}$$

- Given the valley level a, determining p̂*[t] can be done in O(1) time.
- How to find a?
- Note that by conservation of energy

$$\sum_{t=1}^{T-1} \hat{\mathbf{p}}[t] = g(\mathbf{a}) = \sum_{t=1}^{T-1} [\mathbf{a} - \tilde{\mathbf{p}}[t]]_{\underline{\mathbf{r}}[t]}^{\overline{\mathbf{r}}[t]} = c$$

- $g(\mathbf{a})$ is a continuously increasing function of \mathbf{a}
- Bisection algorithm









Valley-filling :
$$\hat{\mathbf{p}}[t] = [\mathbf{a} - \tilde{\mathbf{p}}[t]]^{\bar{\mathbf{r}}[t]}_{\mathbf{r}[t]}$$

- Given the valley level **a**, determining $\hat{\mathbf{p}}^*[t]$ can be done in **O**(1) time.
- How to find a?
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- Solve a using bisection
- For each t, $\hat{\mathbf{p}}[t] = [\mathbf{a} \tilde{\mathbf{p}}[t]]_{\mathbf{r}[t]}^{\bar{\mathbf{r}}[t]}$
- Find W[t] by solving OPF with total demand $\tilde{\mathbf{p}}[t] + \hat{\mathbf{p}}[t]^*$

- Once p̂* is solved, Joint OPF-EV Charging problem
- Complexity reduces from SDP with $O((|\mathcal{N}| + |\mathcal{L}|)(T))$









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Remark

- Once p̂* is solved, Joint OPF-EV Charging problem become decoupled
- Complexity reduces from SDP with $O((|\mathcal{N}| + |\mathcal{L}|)(T))$ variables to T SDPs with $O(|\mathcal{N}| + |\mathcal{L}|)$ variables









Online Scenario

Challenge of the online scenario: $\tilde{\mathbf{p}}[t]$ is not known until time t

Cannot use bisection to solve for a

Strategy: Estimate and adjust

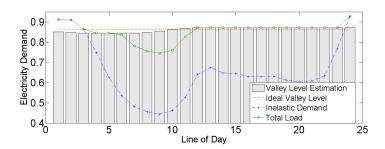
- Estimate a'[1] be the average of total demand
- If $\tilde{\mathbf{p}}[t] + \hat{\mathbf{p}}[t]$ does not reach $\mathbf{a}'[t]$, adjust $\mathbf{a}'[t+1]$ in the opposite direction







Illustration of Dynamic Valley Level Adjustment



- The aggregate charging profile (green line) is valley-filling
- The valley level A'[t] (grey bar) is adjusting dynamical.



- Estimate a'[1] using historical data
- $\hat{\mathbf{p}}[t] = [\mathbf{a}'[t] \tilde{\mathbf{p}}[t]]_{\mathbf{r}[t]}^{\bar{\mathbf{r}}[t]}$
- **3** Find W[t] by solving OPF with total demand $\hat{\mathbf{p}}[t] + \hat{\mathbf{p}}[t]$
- **1** Update $\mathbf{a}'[t+1] = \mathbf{a}'[t] + (\mathbf{a}'[t] \tilde{\mathbf{p}}[t] \hat{\mathbf{p}}[t])/(T-1)$
- Repeat until t = T







Remarks:

- (Theorem 3)The online algorithm will always produce a feasible EV charging schedule.
- - At beginning of each t, utility broadcast valley level A'[t]
 - Each EV determines its charging rate base on A'[t]
 - Utility gather $\hat{\mathbf{p}}[t]$ to calculate next A'[t+1]









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 - At beginning of each t, utility broadcast valley level A'[t]
 - Each EV determines its charging rate base on A'[t]
 - Utility gather $\hat{\mathbf{p}}[t]$ to calculate next A'[t+1]
- In practice, the online algorithm produce charging profiles very close to the offline. optimal

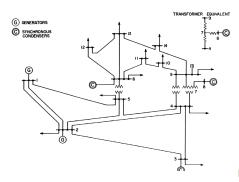






Test cases

- IEEE 14-bus test archive
- SCE residential load for demand variation.



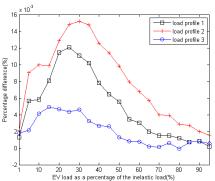






Effect of EV penetration

• Define percentage difference = $(p_{\text{online}}^* - p_{\text{offline}}^*)/p_{\text{online}}^*$

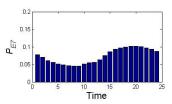


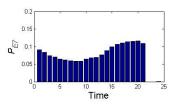
- \bullet Differenece to optimal is very small $\sim 10^{-5}$
- Approaches 0 as penetration goes to 100%





Effect of imperfect first estimation





- (a) Offline solution for EV no. 7 (b) Online solution for EV no. 7
- The charging profiles are still similar
- An initial over-estimation cause EV to charge quicker than optimal
- Finish charging two time slots before deadlines







Table: Performance Comparison

T	SDP Optimization	Offline Algorithm	Online Algorithm
6	6.02 s	5.84 s	5.87 s
12	13.11 s	11.63 s	11.56 s
24	31.47 s	22.87 s	22.81 s
48	84.05 s	45.75 s	45.67 s
96	262.55 s	87.48 s	87.36 s

- Both online and offline algorithms scale linearly to T.
- Gain from the decomposition approach becomes more significant as T increases.



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Summary

In this work, we

- Studied the Joint OPF-EV Charging Problem
- Characterized the optimal EV charging profile
- Proposed an online decentralized algorithm
- The following remains interesting for further investigation
 - Stochastic arrival of EVs.
 - Real time varying EV charing cost







For Further Reading I



J. Lavaei and S. Low.

Zero duality gap for optimal power flow problem. *IEEE Trans. Power Syst.* vol. 27, no. 1, pp. 92-107, Feb. 2012.



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Optimal charging of plug-in hybrid electric vehicles in smart grids.

Proc. IEEE Power and Energy Society General Meeting, pp. 1-6, Jul. 2011.





