

An Analysis of the Multi-Period Optimal Power Flow Problem with Electric Vehicles under Emission Considerations

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- | Classical Optimal Power Flow
- | Second-Order Cone Programming
- | Multi-Period Optimal Power Flow with Electric Vehicles

Problem Definition

SOCP Formulation

Solution Approach

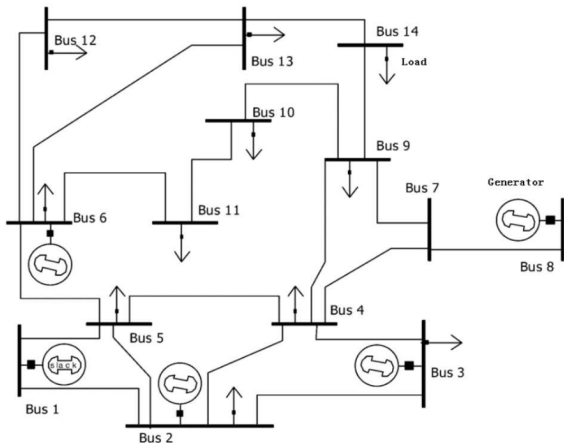
Computational Results

CLASSICAL OPTIMAL POWER FLOW PROBLEM

Optimal Power Flow Problem

- | Aim: To supply electricity to all loads
- | Objective Function: Minimization of generation cost
- | Equality Constraints:
 - Power balance equations
 - Power flow equations
- | Inequality Constraints:
 - Network operating limits

Figure 1: IEEE 14-bus network



Introduction

PARAMETERS

For generator $i \in G$:

Active limit: $\underline{p}_i; \bar{p}_i$

Reactive limit: $\underline{q}_i; \bar{q}_i$

For bus $i \in B$:

Load: $p_i^d; q_i^d$

Voltage limit: $\underline{V}_i; \bar{V}_i$

Shunt: $g_{ij}; b_{ij}$

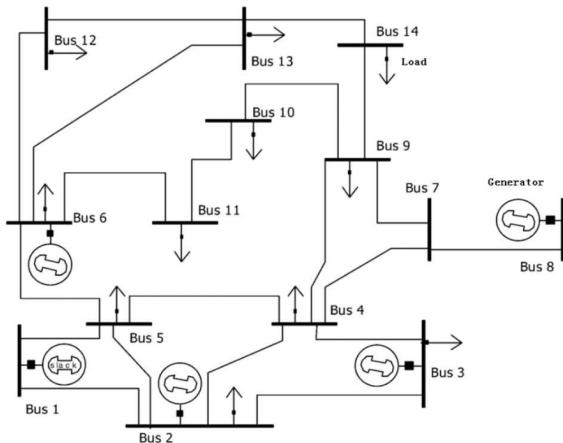
For line $(i; j) \in L$:

Flow limit: \bar{S}_{ij}

Angle limit: θ_{ij}

Admittance: $G_{ij}; B_{ij}$

Figure 1: IEEE 14-bus network



Introduction

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For bus $i \in B$:

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For line $(i;j) \in L$:

Flow limit: \bar{S}_{ij}

Angle limit: θ_{ij}

Admittance: $G_{ij}; B_{ij}$

DECISION VARIABLES

For generator $i \in G$:

Active output: p_i^g

Reactive output: q_i^g

For bus $i \in B$:

Voltage: V_i

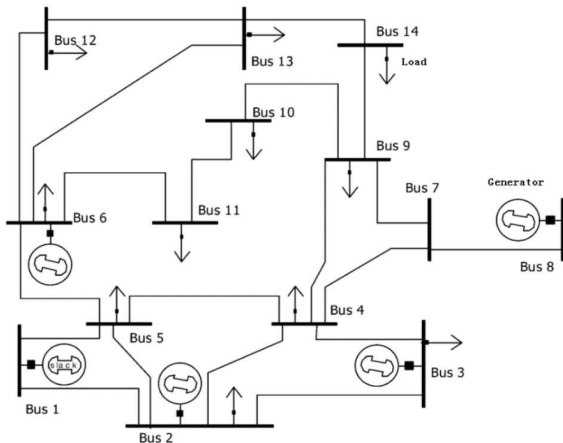
Angle: θ_i

For line $(i;j) \in L$:

Active flow: p_{ij}

Reactive flow: q_{ij}

Figure 1: IEEE 14-bus network



OPF Polar Formulation

$$\begin{aligned}
 & \min \sum_{i \in \mathcal{G}} h(p_i^g) \\
 & \text{s.t. } p_i^g \quad p_i^d = g_{ii} V_i^2 + \sum_{j \in \delta(i)} p_{ij} \quad \left. \begin{array}{l} i \in B \\ i \in B \end{array} \right\} \text{Power balance} \\
 & \quad q_i^g \quad q_i^d = b_{ii} V_i^2 + \sum_{j \in \delta(i)} q_{ij} \\
 & p_{ij} = G_{ij} V_i V_j + j V_i V_j [G_{ij} \cos(\theta_i - \theta_j) - B_{ij} \sin(\theta_i - \theta_j)] \quad (i,j) \in L \\
 & q_{ij} = B_{ij} V_i V_j - j V_i V_j [B_{ij} \cos(\theta_i - \theta_j) + G_{ij} \sin(\theta_i - \theta_j)] \quad (i,j) \in L \\
 & \underline{V}_i \leq V_i \leq \bar{V}_i \quad i \in B \quad \left. \vphantom{\underline{V}_i} \right\} \text{Voltage limit} \\
 & j \in \delta(i) \quad \bar{V}_j \leq V_j \leq \bar{V}_j \quad (i,j) \in L \\
 & p_{ij}^2 + q_{ij}^2 \leq \bar{S}_{ij}^2 \quad (i,j) \in L \\
 & \underline{p}_i \leq p_i^g \leq \bar{p}_i \quad i \in G \\
 & \underline{q}_i \leq q_i^g \leq \bar{q}_i \quad i \in G: \quad \left. \vphantom{\underline{q}_i} \right\} \text{Operational limits}
 \end{aligned}$$

The alternative formulation is first introduced in [1].

New Decision Variables:

- | For each bus $i \in B$,

$$c_{ii} := jV_i^2.$$

- | For each line $(i;j) \in L$,

$$c_{ij} := jV_i V_j \cos(\theta_i - \theta_j)$$

$$s_{ij} := jV_i V_j \sin(\theta_i - \theta_j)$$

OPF Alternative Formulation

$$\min \sum_{i \in G} h(p_i^g)$$

$i \in G$

$$\text{s.t. } p_i^g \quad p_i^d = g_{ii} C_{ii} + \sum_{j \in \mathcal{L}(i)} p_{ij}$$

$$q_i^g \quad q_i^d = b_{ii} C_{ii} + \sum_{j \in \mathcal{L}(i)} q_{ij}$$

$$p_{ij} = G_{ij} C_{ii} + G_{ij} C_{jj} - B_{ij} S_{ij}$$

$$q_{ij} = -B_{ij} C_{ii} - B_{ij} C_{jj} + G_{ij} S_{ij}$$

$$\underline{V}_i^2 \leq C_{ii} \leq \overline{V}_i^2$$

$$C_{ij}^2 + S_{ij}^2 = C_{ii} C_{jj}$$

$$\angle_j - \angle_i = \text{atan2}(S_{ij}; C_{ij})$$

Operational Limits

$$i \in \mathcal{B} \cup \mathcal{G}$$

Power balance

$$i \in \mathcal{B}$$

Power flow

$$(i; j) \in \mathcal{L}$$

$$(i; j) \in \mathcal{L}$$

Voltage limit

$$i \in \mathcal{B}$$

$$(i; j) \in \mathcal{L}$$

Consistency

$$(i; j) \in \mathcal{L}$$

OPF Challenges

- | Network size
- | Problem is nonlinear and nonconvex
- | Locally optimal solutions exist in many OPF test cases [2].
- | Local solvers do not guarantee global optimality.

Convex relaxations based on Semidefinite Programming and/or Second-Order Cone Programming may produce globally optimal solutions or provide valuable dual bounds.

SECOND-ORDER CONE PROGRAMMING

Second-Order Cone Programming

| $\|x\|_2$ is Euclidean norm: $\|x\|_2 = \sqrt{\sum_{i=1}^n x_i^2}$

Second-Order Cone Programming

- | $\|x\|_2$ is Euclidean norm: $\|x\|_2 = \sqrt{\sum_{i=1}^n x_i^2}$
- | Second order cone: $f(x; t) : \|x\|_2 \leq t$

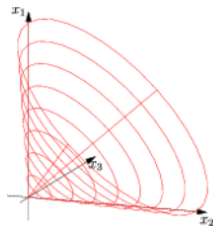
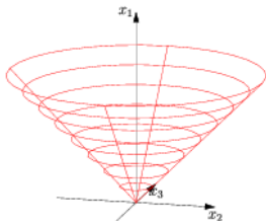
Second-Order Cone Programming

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| Examples: $\sqrt{x_2^2 + x_3^2} \leq x_1$

Rotated cone: $x_3^2 \leq 2x_1x_2$

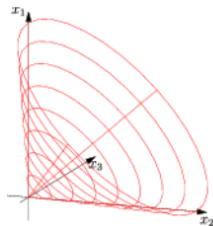
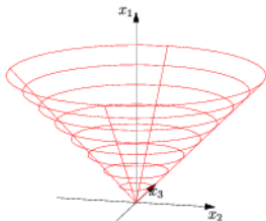


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| Second Order Cone Programming (SOCP):

$$\begin{aligned} \min \quad & f^T x \\ \text{s.t.} \quad & \|A_i x + b_i\|_2 \leq c_i^T x + d_i \quad i = 1; \dots; m \end{aligned}$$

SOCP Relaxation of the OPF Alternative Formulation

$$\begin{aligned}
 & \min \sum_{i \in G} h(p_i^g) \\
 & \text{s.t. } p_i^g - p_i^d = g_{ii} c_{ii} + \sum_{j \in \mathcal{B} \setminus \{i\}} p_{ij} \\
 & \quad q_i^g - q_i^d = b_{ii} c_{ii} + \sum_{j \in \mathcal{B} \setminus \{i\}} q_{ij} \\
 & \quad p_{ij} = G_{ij} c_{ii} + G_{ij} c_{jj} - B_{ij} s_{ij} \\
 & \quad q_{ij} = B_{ij} c_{ii} - B_{ij} c_{jj} + G_{ij} s_{ij} \\
 & \quad \underline{V}_i^2 \leq c_{ii} \leq \overline{V}_i^2 \\
 & \quad c_{ij}^2 + s_{ij}^2 \leq c_{ii} c_{jj} \\
 & \quad \tan^{-1} \left(\frac{s_{ij}}{c_{ij}} \right) = \text{atan2}(s_{ij}, c_{ij}) \\
 & \quad \text{Operational Limits}
 \end{aligned}$$

$i \in \mathcal{B}$
 $i, j \in \mathcal{B}$
 $(i, j) \in \mathcal{L}$
 $(i, j) \in \mathcal{L}$
 $i \in \mathcal{B}$
 $(i, j) \in \mathcal{L}$
 $(i, j) \in \mathcal{L}$

Power balance
 Power flow
 Voltage limit
 Relaxation!

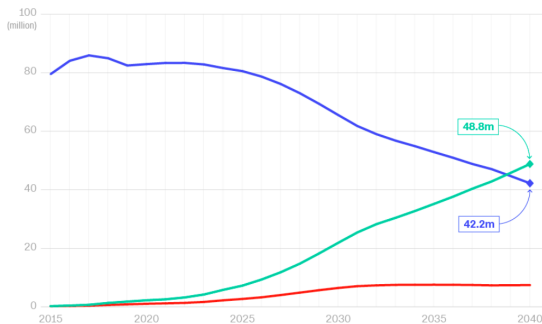
MULTI-PERIOD OPTIMAL POWER FLOW PROBLEM WITH ELECTRIC VEHICLES

Multi-Period Optimal Power Flow (MOPF) Problem

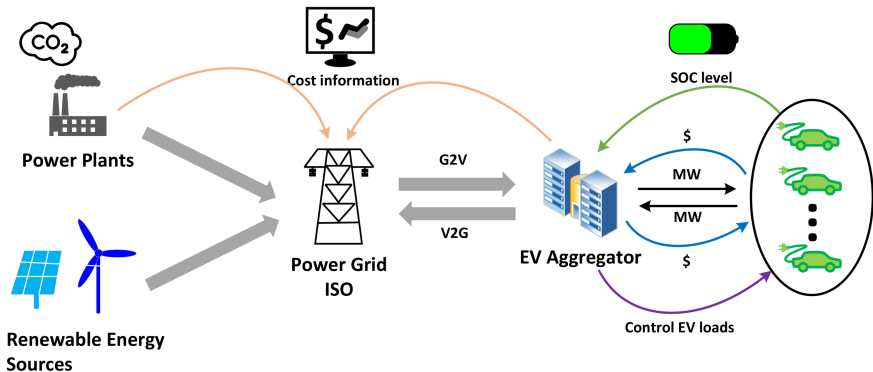
- | Number of EVs: 3.3 million in 2018 / 4.8 million in 2019
- | Governments incentives + falling EV prices
- | In 2040s, the number of EVs will be more than conventional vehicles.

By 2040, electric cars could outsell gasoline and diesel

— Internal combustion engine vehicles — Battery electric vehicles — Plug-in hybrid electric vehicles



MOPF with EVs under Emission Considerations



- | A new MOPF formulation
- | Real datasets: electricity demand and EV driving profiles
- | Emission considerations
- | Global optimal solutions with very small optimality gaps even in large scale networks
- | Computational results show that:

Marginal emissions can be significantly reduced, keeping cost constant.

V2G can save cost despite assuming hourly electricity prices are constant.

SOCP Relaxation of MOPF Formulation

Additional variables and parameters for each bus $i \in B$ and time $t \in T$:

- | Charging and discharging power: $a_{it}; b_{it}$
- | EV battery stock variable: s_{it}
- | Maximum allowable charging and discharging power: $\bar{a}_{it}; \bar{b}_{it}$
- | Min energy requirement and max capacity of EV battery: $\underline{s}_{it}; \bar{s}_{it}$
- | Charging efficiency: η_i
- | Initial battery state of charge (SOC): l_i
- | Marginal emission parameter: e_t
- | “Reference” power generation without any EVs (used to compute marginal emissions): \bar{p}_{it}^g
- | Total marginal emission limit: \bar{E}

SOCP Relaxation of MOPF Formulation

Additional EV related constraints:

$$\min_{t \in \{2, \dots, T\}; i \in \{2, \dots, G\}} h(p_{it}^g)$$

$$\text{s.t. } S_{it} + \sum_{j \in B} a_{ijt} b_{jt} - c_{it} = S_{i(t+1)}$$

$$\underline{S}_{it} \leq S_{it} \leq \bar{S}_{it}$$

$$S_{i0} = I_j \bar{S}_{i0}$$

$$S_{i(T+1)} = I_j \bar{S}_{i(T+1)}$$

$$0 \leq a_{ijt} \leq \bar{a}_{ijt}$$

$$0 \leq b_{ijt} \leq \bar{b}_{ijt}$$

$$\sum_{i \in B} e_{it}(p_{it}^g) \leq \bar{E}$$

$$i \in B; t \in T$$

$i \in B; t \in \{0, \dots, T\}$ Stock

$i \in B; t \in T$ Stock limit

$i \in B$ Initial battery SOC

$i \in B; t \in T$ Charging limit

Emission limit

SOCP Relaxation of MOPF Formulation (cont.)

$$p_{it}^g - p_{it}^d - \underline{a}_{it} + \overline{a}_{it} + \underline{b}_{it} = g_{ii} c_{iit} + \sum_{j \in \mathcal{J}(i)} p_{ijt}$$

$$q_{it}^g - q_{it}^d = b_{ii} c_{iit} + \sum_{j \in \mathcal{J}(i)} q_{ijt}$$

$$p_{ijt} = G_{ij} c_{iit} + G_{ij} c_{ijt} - B_{ij} s_{ijt}$$

$$q_{ijt} = B_{ij} c_{iit} - B_{ij} c_{ijt} + G_{ij} s_{ijt}$$

$$\underline{V}_i^2 \leq c_{iit} \leq \overline{V}_i^2$$

$$c_{ijt}^2 + s_{ijt}^2 \leq c_{iit} c_{ijt}$$

$$p_{ijt}^2 + q_{ijt}^2 \leq \overline{S}_{ij}^2; \quad j \in \mathcal{I}(i) \quad i, j \in \mathcal{N}$$

$$\underline{p}_i \leq p_{it}^g \leq \overline{p}_i; \quad \underline{q}_i \leq q_{it}^g \leq \overline{q}_i$$

$$i \in \mathcal{B}; t \in \mathcal{T}$$

$$i \in \mathcal{B}; t \in \mathcal{T}$$

$$(i; j) \in \mathcal{L}; t \in \mathcal{T}$$

$$(i; j) \in \mathcal{L}; t \in \mathcal{T}$$

$$i \in \mathcal{B}; t \in \mathcal{T}$$

$$(i; j) \in \mathcal{L}; t \in \mathcal{T}$$

$$i \in \mathcal{B}; t \in \mathcal{T}$$

Power balance

Power flow

Voltage limit

Consistency

Operational limits

We combine the following datasets to suggest practical solutions to cope with possible grid challenges:

- | OPF instance
- | Hourly electricity demand
- | Marginal emission factors
- | EV driving profiles

Realistic OPF instance from the PG-OPF library.

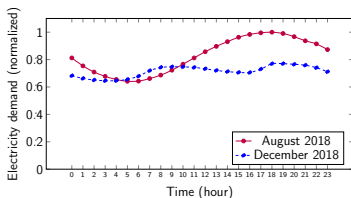
- | Illinois 200-bus system
- | South Carolina 500-bus system
- | Texas 2000-bus system

Note from [3]: “These test cases are entirely synthetic, built from public information and a statistical analysis of real power systems. It bears no relation to the actual grid in this location, except that generation and load profiles are similar.”

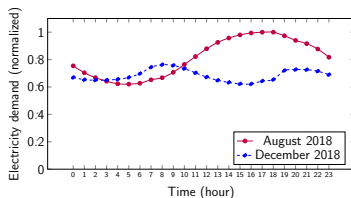
Input - Hourly Electricity Demand

Hourly electricity demand obtained from Energy Information Administration (EIA) is normalized by the maximum demand.

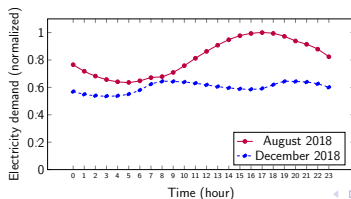
(a) Illinois 200-bus



(b) South Carolina 500-bus



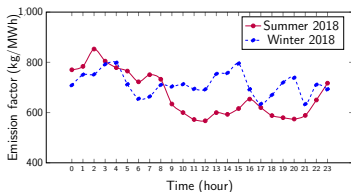
(c) Texas 2000-bus



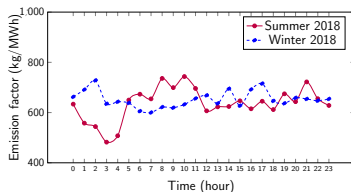
Input - Marginal Emission Factors

Marginal emission factors from the Climate and Energy Decision Making Center

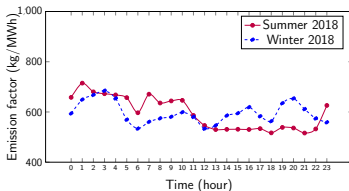
(a) Illinois 200-bus



(b) South Carolina 500-bus

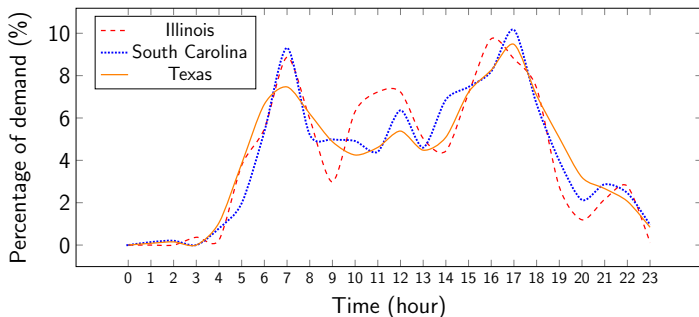


(c) Texas 2000-bus



We use the National Household Travel Survey (NHTS) to obtain driving profiles.

Figure 4: Percentage of EV demand by time of day.



Solution Approach

Solution Approach

To obtain a lower bound: solve the SOCP relaxation (with Gurobi)

Fix the charging and discharging variables in the NLP model

To obtain an upper bound: solve the OPF problem (with IPOPT)

Compute optimality gap

Repeat this procedure for different "Total marginal emission limit"s

Computational Results

Table 1: Input data and parameter settings.

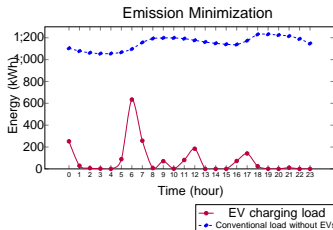
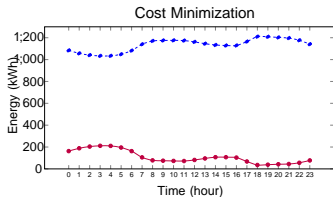
Settings	
Region	Illinois South Carolina Texas
Season	Winter Summer
Initial battery SOC	0% max%
Direction of flow	only G2V G2V and V2G

We compare the results of our optimization model with a simple BENCHMARK: Start charging the EV battery at midnight until it is charged enough or until its first trip.

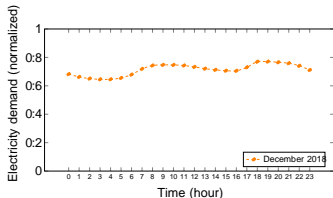
Optimality gap of Illinois 200-bus instance is less than 5% for all cases.

Hourly Load Variations

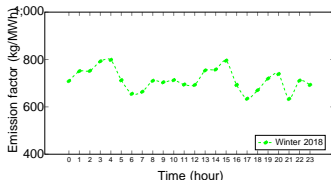
Figure 5: Illinois (200-bus system) in winter SOC=0%, only G2V.



(a) Hourly Electricity Demand

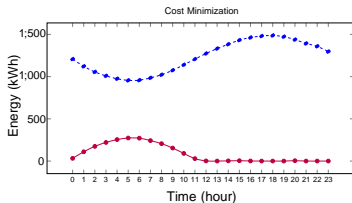


(b) Hourly Emission Factor

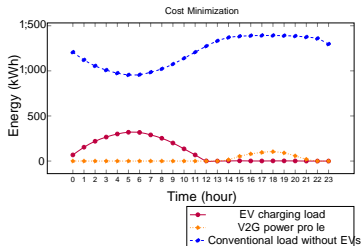


Effect of V2G for summer and winter (200-bus Illinois)

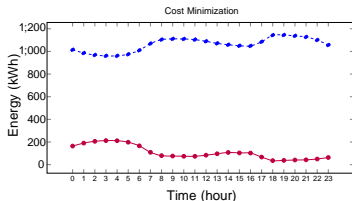
(a) Only G2V summer



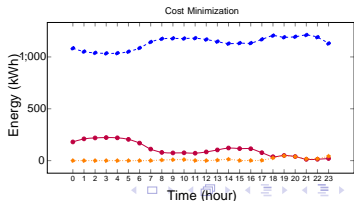
(b) G2V and V2G summer



(c) Only G2V winter

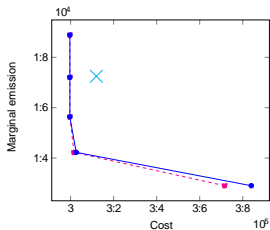


(d) G2V and V2G winter

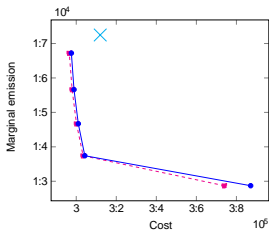


Total Cost vs. Marginal Emission

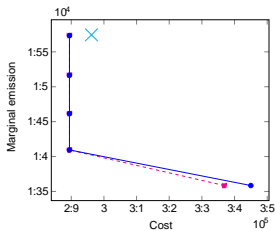
(a) only G2V summer



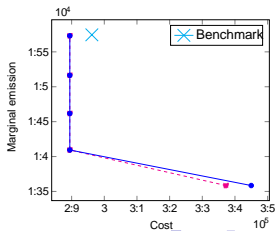
(b) G2V and V2G summer



(c) only G2V winter

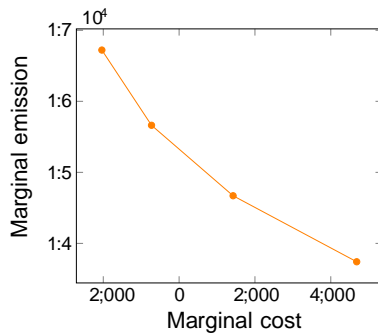


(d) G2V and V2G winter



Marginal Cost vs. Marginal Emission

Figure 10: V2G and G2V summer



Conclusions

- | We proposed a new MOPF formulation with EV and emission considerations
- | We combined different datasets (grid data, hourly demand, marginal emissions and driving profiles) to model the problem as realistically as possible
- | Our SOCP-based algorithm provides (almost) globally optimal solutions with very small optimality gaps even in large scale networks
- | Computational results showed that:
 - Marginal emissions can be significantly reduced, keeping cost constant.
 - V2G can save cost despite assuming hourly electricity prices are constant.

Optimality Gaps for MOPF

South Carolina 500-bus between 3.9 % and 6.4 %
Texas 2000-bus less than 0.7%

- [1] A. G. Expósito and E. R. Ramos, “Reliable load flow technique for radial distribution networks,” *IEEE Transactions on Power Systems*, vol. 14, no. 3, pp. 1063–1069, 1999.
- [2] W. A. Bukhsh, A. Grothey, K. I. McKinnon, and P. A. Trodden, “Local solutions of the optimal power flow problem,” *IEEE Transactions on Power Systems*, vol. 28, no. 4, pp. 4780–4788, 2013.
- [3] A. B. Birchfield, T. Xu, K. M. Gegner, K. S. Shetye, and T. J. Overbye, “Grid structural characteristics as validation criteria for synthetic networks,” *IEEE Transactions on Power Systems*, vol. 32, no. 4, pp. 3258–3265, 2017.