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Title
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Microgrid modeling using the stochastic Distributed Energy Resources Customer Adoption Model DER-CAM*)

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Outline

• Motivation
• The Distributed Energy Resources Customer Adoption Model (DER-CAM)
• DER-CAM stochastic formulation
• EV fleet aggregator
• Case study
• Results
• Conclusions and next steps
Motivation

Increasing penetration of electric vehicles (EVs) creates DER potential

Impact on optimal DER investment decisions
Motivation

Optimization determines the energy flow direction, microgrid could perform load management.
Motivation: the microgrid / energy flow

- solar PV
- solar heat
- alternative fuel vehicles
- electricity storage
- combined heat & power
- heat storage
- commercial biofuels
- on-site biofuels
- geothermal heat

End uses:
- electric only
- refrigeration + building cooling
- building heating
- hot water
- gas or liquid fuels only

Key:
- energy losses
• is a Mixed Integer Linear Program (MILP), written in the General Algebraic Modeling System (GAMS®)

• minimizes annual energy costs, CO₂ emissions, or multiple objectives of providing services to a building

• produces technology neutral pure optimal results, delivering investment decisions and the operational schedule

• has been developed for more than 10 years by Berkeley Lab and collaborations in the US, Germany, Spain, Portugal, Belgium, Japan, and Australia

• first commercialization and real-time optimization steps, e.g. Distributed Energy Resources Web Optimization Service (WebOpt)
  http://der.lbl.gov/der-cam/how-access-der-cam
DER-CAM

Example Constraints
- energy balance – supply & demand
- financial – payback
- technical – roof area for PV

Customer Load
- hourly by enduse

Market Info
- tariffs, fuel prices

DER Technology Info
- generation, solar collection, & CHP

Optimal Technology Choices

Other Outputs
- i.e., costs, energy use, emissions

Energy Sales

Hourly Optimal Operating Schedule

DR Input Parameter
Uncertainty

Several sources of uncertainty can affect optimal DER investment decisions:

- energy loads
- renewable output
- market prices
- outages (grid and DER)
- EV driving patterns

This motivates the need for a stochastic implementation of DER-CAM:

→ this work: uncertainty in EV driving schedules
→ generic implementation, other sources of uncertainty can be considered
Stochastic formulation of DER-CAM

Two-stage stochastic problem
- first stage → investment decisions; yes or no? How much capacity?
- second stage → operation decisions; charge or discharge? unit commitment?

Objective function (generic structure), deterministic equivalent problem

$$\min C = \sum_{m} Fix_m + \sum_{i} Inv_i \cdot InvCost_i + \sum_{\omega} p_\omega \cdot \sum_{m} \sum_{t} \sum_{h} OpCost_{\omega,m,t,h}$$

- $Fix_m$ fixed costs in month $m$
- $Inv_i$ investment decision on technology I, continuous versus discrete technologies
- $InvCost_i$ annualized investment cost of technology $i$
- $p_\omega$ probability of scenario $\omega$
- $OpCost_{\omega,m,t,h}$ microgrid operation costs in scenario, month $m$, day type $t$, hour $h$
the microgrid EV costs include:

- investments in EV infrastructure ($1000$/car, 10 years lifetime)

- battery degradation costs: losses in the battery lifetime induced by the microgrid
  (scenario $\omega$; month $m$; weekday $t$; hour $h$)

$$evbatcost_{\omega,m,t,h} = RCost \cdot Closs \cdot (eievh_{\omega,m,t,h} + eoevh_{\omega,m,t,h} + eievu_{\omega,m,t,h} + eoevu_{\omega,m,t,h})$$

- $RCost$ battery replacement cost, $$/kWh$
- $Closs$ capacity loss per normalized kWh
- $eievh$ input to EVs at Home (and not used for driving)
- $eoevh$ output From EVs at home
- $eievu$ input to EVs at the microgrid (and not used for driving)
- $eoevu$ output from EVs at the microgrid

- home electricity exchange costs induced by the microgrid

$$evhcost_{\omega,m,t,h} = pEV \cdot \left(\frac{eievh_{\omega,m,t,h}}{\eta_c} - eoevh_{\omega,m,t,h} \cdot \eta_{dc}\right)$$

- $pEV$ electricity price at Home
- $\eta_c$ EV battery charging efficiency
- $\eta_{dc}$ EV battery discharging efficiency
Key assumptions

- no battery subsidies are paid by the microgrid
- all benefits are allocated to the microgrid
- all inefficiencies are allocated to the microgrid
- EV owner purchases car anyway and has no disadvantage due to microgrid
- *non-dimensional fleet distribution introduces uncertainty*
- electricity used for driving is not considered in microgrid energy costs
- all cars charge enough electricity at home for a daily roundtrip
- driving electricity can be used by the microgrid but must be returned
EV fleet aggregator

Possible states, \( i = \{H, Tu, Th, U\} \)
- \( H \) - Home
- \( Tu \) - In Traffic to uGrid
- \( Th \) - In Traffic to Home
- \( U \) - uGrid
Parameters
a) fleet distribution
b) fleet transitions

Key decision variables
c) EV fleet size
d) electric input / output at home and uGrid

Other variables
e) electricity stored at home and uGrid
f) driving consumption
g) electricity stored in traffic
Case study

- large office Building in San Francisco
- 2.3 MW electric peak

Possible technologies
- internal combustion engines, micro-turbines, gas turbines, fuel cells, heat exchangers, PV, solar thermal, absorption chillers, stationary electric storage, and electric vehicles

Cost optimization runs
- no DER investments
- invest without EVs
- invest with Evs
- deterministic and stochastic
- max. payback period: 5 and 12 years
Case study - source of uncertainty

EV fleet distribution obtained from a 2009 US survey on departure times for daily commute round trips

Case study - source of uncertainty

not all cars are considered in the daily departure distribution: driving scenarios obtained by maximizing time at the uGrid (S1), at home (S3), and using the average (S2)

Case study - statistics

GAMS 23.0.2; CPLEX 11.2.1
max. resolution time: 10h; max. iterations: 5 000 000; optimality gap: 0.1%

<table>
<thead>
<tr>
<th>model options</th>
<th>equations</th>
<th>variables</th>
<th>discrete variables</th>
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BAU – no investments; NOEV – invest without EVs; EV – invest in EV infrastructure; S1/S2/S3 – fleet distribution scenario; ST – stochastic mode; P5/P12 – maximum payback
## Case study – key results

<table>
<thead>
<tr>
<th>run</th>
<th>total energy costs (k$)</th>
<th>total CO₂ (t CO₂)</th>
<th>adopted capacity (kW)</th>
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<th>total CO₂ (kg CO₂)</th>
<th>adopted capacity (kW)</th>
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<td>PV</td>
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<tr>
<td>EVSTP12</td>
<td>1 582</td>
<td>4 250</td>
<td>970</td>
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</table>
Case study – key results

- EVs are used during the day when electricity prices are highest.
- Optimal scheduling behavior includes using the EV batteries for load shifting.
- Utility purchase is kept mostly flat, avoiding high power demand charges.
- ICE adopted are also used to charge the EV batteries (increases capacity factors).
Effect of uncertainty in dispatch

Microgrid Dispatch, August, EVSTP5

- Original Electric Load
- EV Output, S1
- EV Output, S2
- EV Output, S3
- DG, S1
- DG, S2
- DG, S3
- Utility Purchase, S1
- Utility Purchase, S2
- Utility Purchase, S3

0 500 1000 1500 2000 2500

0 1 25 49 73 97 121 145

kW

Hour
Case study – key results

- charge batteries at home and use the electricity at the microgrid throughout the day (home charging rate: 6c/kWh, microgrid: >> 10c/kWh)
- charging occurs in early morning hours, both at home and at the microgrid
Case study – key results

- The introduction of EVs leads to financial savings and CO₂ emission reductions both with 5 and 12 year payback periods.

- The total energy costs in sets (5 and 12 yr. paybacks) tend to be similar once EVs are allowed in the runs.

- The energy cost reductions achieved by considering the use of EVs are most significant in lower payback periods.

- With lower payback periods adding EVs significantly changes the optimal investment solution by introducing a 250kW ICE coupled with heat exchangers.

- The use of the integrated approach in DER-CAM allows capturing indirect effects, as the ICE would not be adopted in the absence of EVs.
Conclusions and next steps

- the market conditions analyzed in this work lead to a predominant behavior where EVs are charged at home and used later at the microgrid in order to reduce energy costs

- considering uncertainty in the EV driving schedules introduces little changes in total energy costs, indicating that EVs have a high DER potential and should be considered in investment decisions

- little impact of uncertainty due to large building size

→ analyze smaller sized buildings
→ introduce other sources of uncertainty, such as renewable output
→ introduce time-of-use tariffs for home electricity exchanges
→ different departure distributions for different days
Thank you

Contact Info:

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Key inputs
energy loads – electricity, cooling, heating, …
technology costs – capital costs, maintenance costs, …
technology specs – rated capacity, electric efficiency, heat / power ratio, lifetime, …
utility info – electricity/NG tariffs (time of use, demand charges), marginal CO₂, …

Available technologies
reciprocating engines, micro-turbines / gas turbines, fuel cells, heat exchanger / CHP, PV, solar thermal, absorption chillers, heat pumps, electric storage, electric vehicles

Key features
technology integration, cooling offset, multi-objective optimization, NZEB, …

Key outputs
installed capacity, operating schedule, energy costs, CO₂ emissions, …
### EV fleet aggregator

\[
\begin{align*}
\text{EVFH}_{\omega,m,t,h} &= \text{EVFH}_{\omega,m,t,h-1} + \text{EVFT2H}_{\omega,m,t,h} - \text{EVFH2T}_{\omega,m,t,h} \\
\text{EVFTU}_{\omega,m,t,h} &= \text{EVFTU}_{\omega,m,t,h-1} + \text{EVFH2T}_{\omega,m,t,h} - \text{EVFT2U}_{\omega,m,t,h} \\
\text{EVFT2H}_{\omega,m,t,h} &= \text{EVFT2H}_{\omega,m,t,h-1} + \text{EVFU2T}_{\omega,m,t,h} - \text{EVFT2H}_{\omega,m,t,h} \\
\text{EVFU}_{\omega,m,t,h} &= \text{EVFU}_{\omega,m,t,h-1} + \text{EVFT2U}_{\omega,m,t,h} - \text{EVFU2T}_{\omega,m,t,h} \\
\end{align*}
\]

**States**
- \(\text{EVFH}_{\omega,m,t,h}\): share of total fleet at home in scenario \(\omega\), month \(m\), daytype \(t\), hour \(h\)
- \(\text{EVFTU}_{\omega,m,t,h}\): share of total fleet in traffic to uGrid in...
- \(\text{EVFU}_{\omega,m,t,h}\): share of total fleet at uGrid in...
- \(\text{EVFT2H}_{\omega,m,t,h}\): share of total fleet in traffic to home in...

**Transitions**
- \(\text{EVFH2T}_{\omega,m,t,h}\): share of total fleet that goes from home to traffic in scenario \(\omega\), month \(m\), daytype \(t\), hour \(h\)
- \(\text{EVFT2U}_{\omega,m,t,h}\): share of total fleet that arrives at uGrid from traffic in...
- \(\text{EVFU2T}_{\omega,m,t,h}\): share of total fleet that goes from the uGrid to traffic in...
- \(\text{EVFT2H}_{\omega,m,t,h}\): share of total fleet that arrives at home from traffic in...
**EV fleet aggregator**

**Electricity in cars at home** = electricity in cars at home in the previous hour – electricity in cars that left + electricity in cars that arrived + input at home – output at home

\[
esevh_{\omega,m,t,h} = \\
= \left( esevh_{\omega,m,t,h-1} \cdot \left( 1 - \frac{EVFH2T_{\omega,m,t,h}}{EVFH_{\omega,m,t,h-1}} \right) \right) + esevh_{\omega,m,t,h-1} \cdot \frac{EVFT2H_{\omega,m,t,h}}{EVFTH_{\omega,m,t,h-1}} \cdot (1 - \varphi_k) + \\
+ eievh_{\omega,m,t,h} - eoevh_{\omega,m,t,h}
\]

**Electricity in cars travelling to the uGrid** = electricity in cars that were travelling to the uGrid in the previous hour – electricity in cars that arrived at the uGrid + electricity in cars coming into traffic + electricity needed for a daily round trip – electricity spent driving to the uGrid

\[
esevtu_{\omega,m,t,h} = \\
= \left( esevtu_{\omega,m,t,h-1} \cdot \left( 1 - \frac{EVFT2U_{\omega,m,t,h}}{EVFTU_{\omega,m,t,h-1}} \right) \right) + esevh_{\omega,m,t,h-1} \cdot \frac{EVFH2T_{\omega,m,t,h}}{EVFH_{\omega,m,t,h-1}} \cdot (1 - \varphi_k) + \\
+ \left( \sum_h \left( EVFTU_{\omega,m,t,h} + EVFTH_{\omega,m,t,h} \right) \cdot \frac{EVFH2T_{\omega,m,t,h}}{\sum_h EVFH2T_{\omega,m,t,h}} - EVFT2U \right) \cdot \frac{cap_k}{EVBat} \cdot EVDC
\]
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