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

Presented by Dr. Michael Stadler

Team: Gonçalo Cardoso, Michael Stadler, Mohammad C. Bozchalui, Ratnesh Sharma, Chris Marnay, Afzal Siddiqui, and Markus Groissböck

Environmental Energy Technologies Division

INFORMS Annual Meeting 2012 Phoenix
15 October 2012

http://emp.lbl.gov/reports

The work described in this presentation was funded by the Office of Electricity Delivery and Energy Reliability, Distributed Energy Program of the U.S. Department of Energy under Contract No. DE-AC02-05CH11231 and partly by NEC Laboratories America Inc
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Microgrid modeling using the stochastic Distributed Energy Resources Customer Adoption Model DER-CAM*)

Dr. Michael Stadler
mstadler@lbl.gov
der.lbl.gov

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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
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
DER-CAM

- 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
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
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 \( h \)
Stochastic formulation of DER-CAM

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 $h$)

$$\text{evbatcost}_{\omega,m,t,h} = \text{RCost} \cdot \text{CLoss} \cdot \left( \text{eiev}_{\omega,m,t,h} + \text{eoev}_{\omega,m,t,h} + \text{eieu}_{\omega,m,t,h} + \text{eoev}_{\omega,m,t,h} \right)$$

- $\text{RCost}$: battery replacement cost, $$/kWh$
- $\text{CLoss}$: capacity loss per normalized kWh
- $\text{eiev}$: input to EVs at Home (and not used for driving)
- $\text{eoev}$: output from EVs at home
- $\text{eieu}$: input to EVs at the microgrid (and not used for driving)
- $\text{eoev}$: output from EVs at the microgrid

- home electricity exchange costs induced by the microgrid

$$\text{evhcost}_{\omega,m,t,h} = p_{EV} \cdot \left( \frac{\text{eiev}_{\omega,m,t,h}}{\eta_c} - \text{eoev}_{\omega,m,t,h} \cdot \eta_{dc} \right)$$

- $p_{EV}$: electricity price at Home
- $\eta_c$: EV battery charging efficiency
- $\eta_{dc}$: EV battery discharging efficiency
EV fleet aggregator

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
EV fleet aggregator

**Parameters**
a) fleet distribution  
b) fleet transitions

d) electric input / output at home and uGrid

c) EV fleet size

d) electric input / output at home and uGrid

e) electricity stored at home and uGrid

**Key decision variables**

**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

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%

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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

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<td>12 506</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, S2
- Utility Purchase, S3
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:

Michael Stadler / mstadler@lbl.gov
DER-CAM

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

\[
\begin{align*}
EVFH_{\omega,m,t,h} & = EVFH_{\omega,m,t,h-1} + EVFT2H_{\omega,m,t,h} - EVFH2T_{\omega,m,t,h} \\
EVFTU_{\omega,m,t,h} & = EVFTU_{\omega,m,t,h-1} + EVFH2T_{\omega,m,t,h} - EVFT2U_{\omega,m,t,h} \\
EVFTU_{\omega,m,t,h} & = EVFTU_{\omega,m,t,h-1} + EVFU2T_{\omega,m,t,h} - EVFT2H_{\omega,m,t,h} \\
EVFU_{\omega,m,t,h} & = EVFU_{\omega,m,t,h-1} + EVFT2U_{\omega,m,t,h} - EVFU2T_{\omega,m,t,h}
\end{align*}
\]

States
- \(EVFH_{\omega,m,t,h}\): share of total fleet at home in scenario \(\omega\), month \(m\), daytype \(t\), hour \(h\)
- \(EVFTU_{\omega,m,t,h}\): share of total fleet in traffic to uGrid in...
- \(EVFU_{\omega,m,t,h}\): share of total fleet at uGrid in...
- \(EVFTH_{\omega,m,t,h}\): share of total fleet in traffic to home in...

Transitions
- \(EVFH2T_{\omega,m,t,h}\): share of total fleet that goes from home to traffic in scenario \(\omega\), month \(m\), daytype \(t\), hour \(h\)
- \(EVFT2U_{\omega,m,t,h}\): share of total fleet that arrives at uGrid from traffic in...
- \(EVFU2T_{\omega,m,t,h}\): share of total fleet that goes from the uGrid to traffic in...
- \(EVFT2H_{\omega,m,t,h}\): share of total fleet that arrives at home from traffic in...

Cars at home = Cars at home in previous hour + cars arriving – cars leaving
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

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

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

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