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

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# Outline

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- 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

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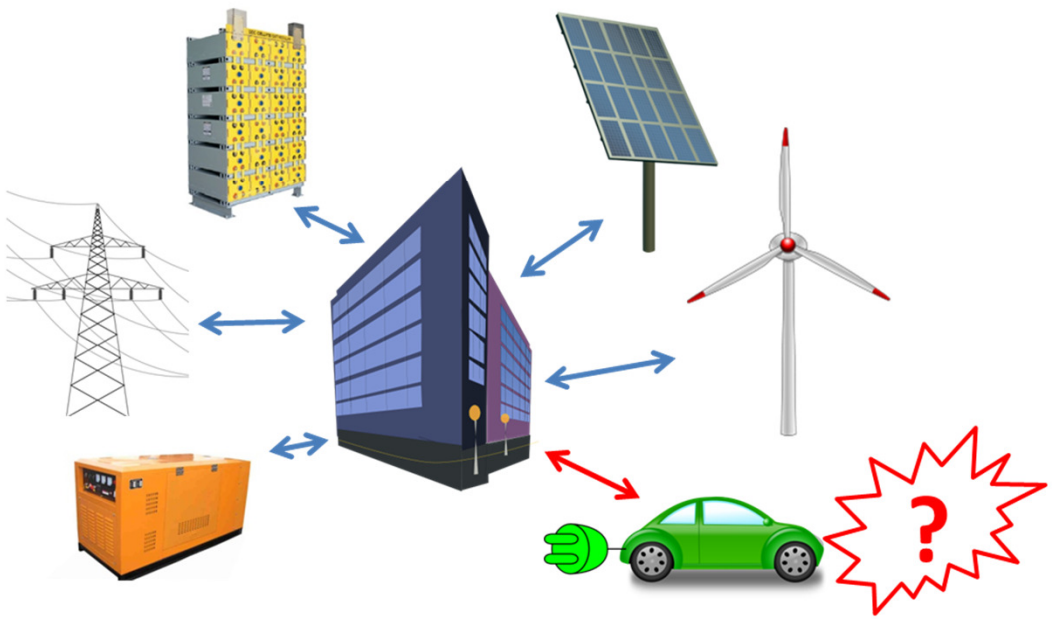
Increasing penetration of electric vehicles (EVs) creates **DER** potential

**Impact on optimal DER investment decisions**



# Motivation

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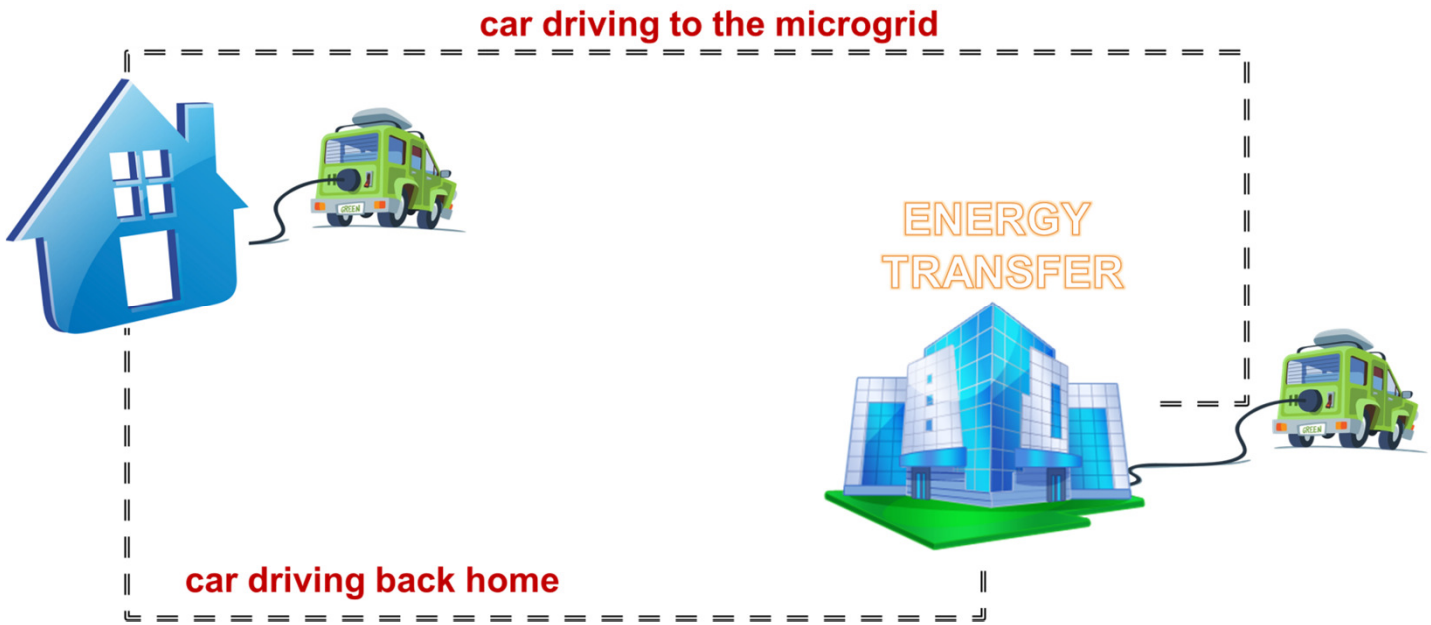


optimization determines the energy flow direction, microgrid could perform load management

# Motivation: the microgrid / energy flow

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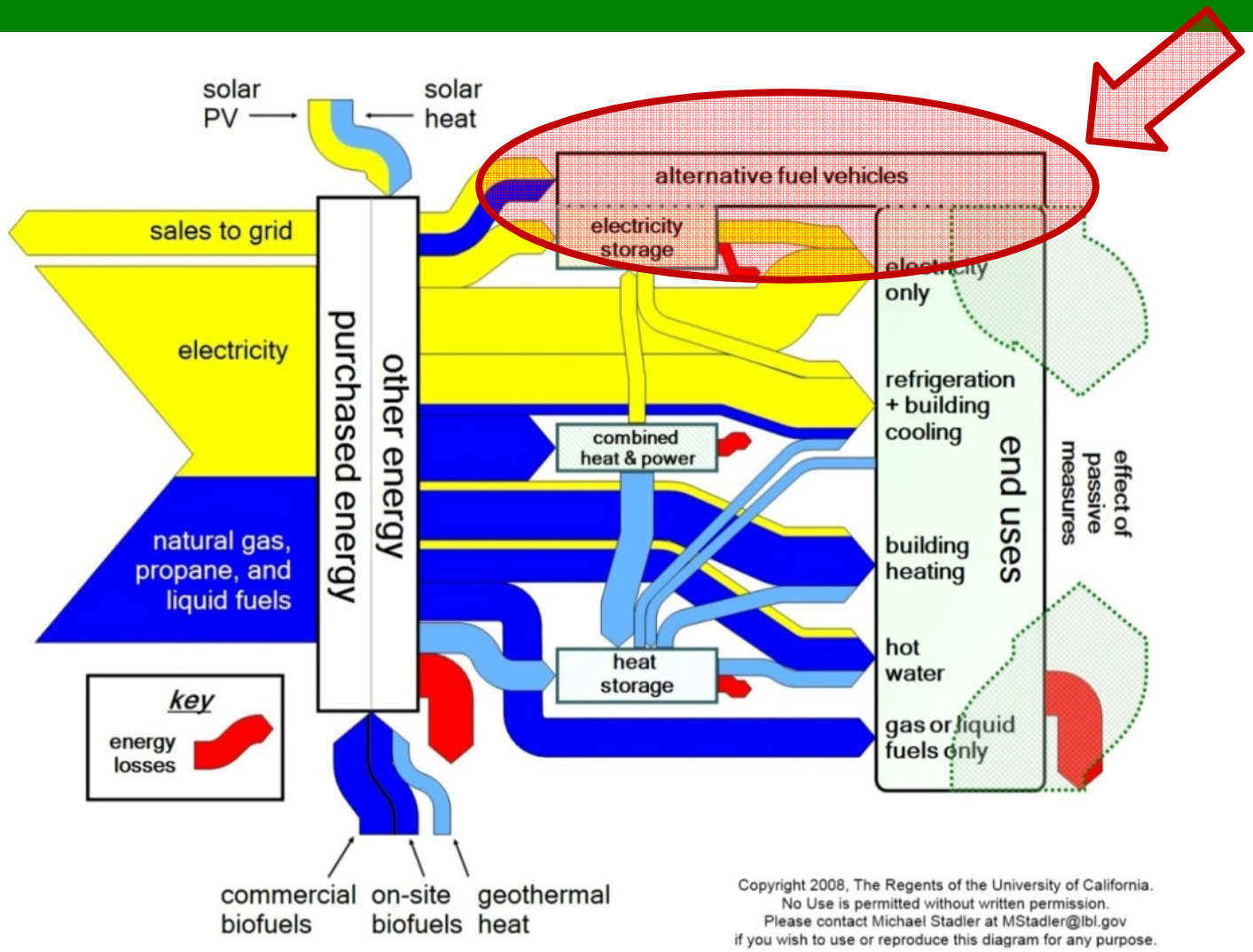


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# DER-CAM

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- is a Mixed Integer Linear Program (MILP), written in the General Algebraic Modeling System (GAMS®)
- minimizes annual energy costs, $CO_2$ 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

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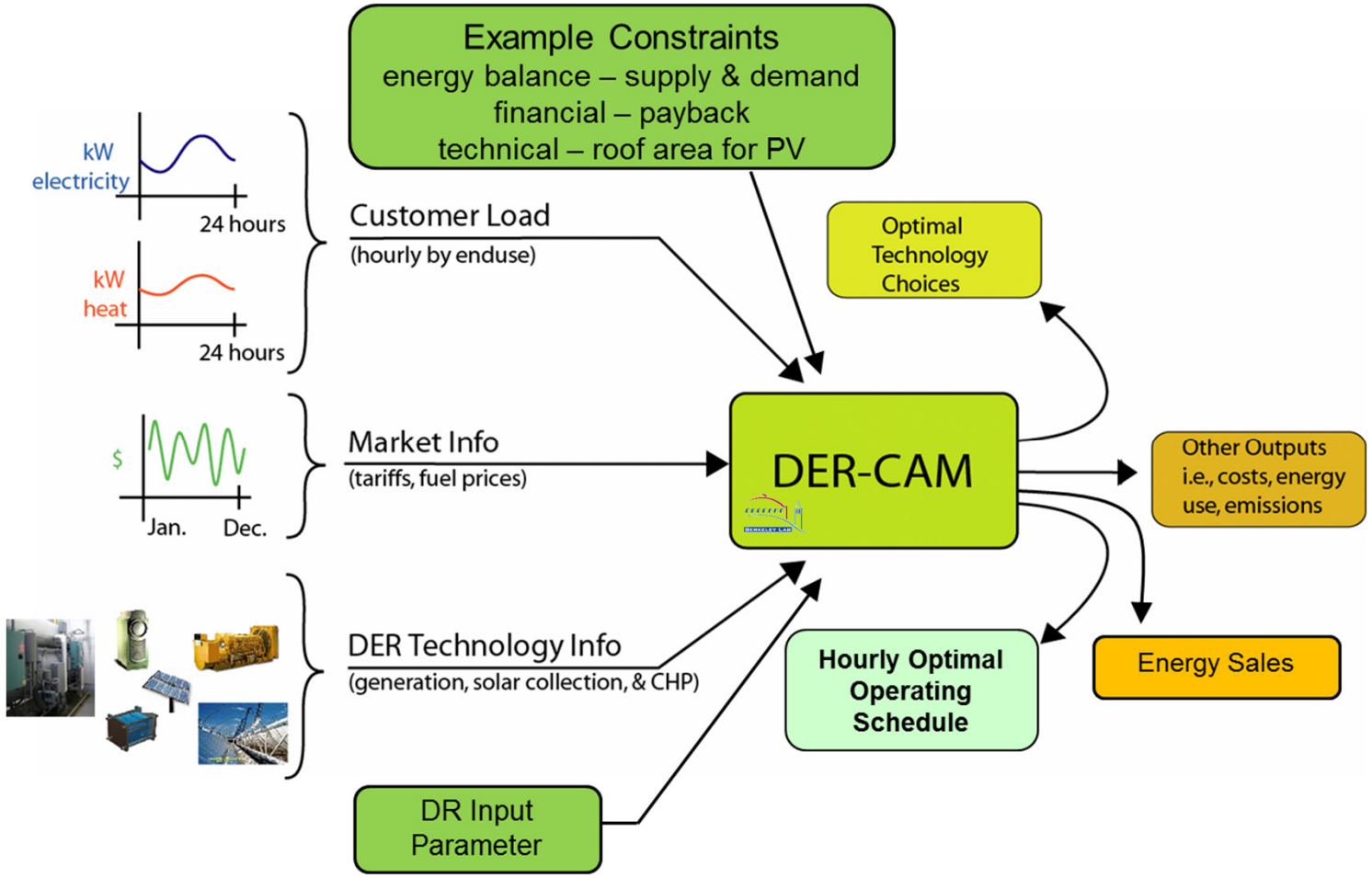

# Uncertainty

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**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

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**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 ω |
| $OpCost_{\omega,m,t,h}$ | microgrid operation costs in scenario, month m, day type t, hour h |

# Stochastic formulation of DER-CAM

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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 $h$)

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

| | |
|---|---|
| $RCost$ | 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

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

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

# EV fleet aggregator

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**Key assumptions**

- no battery subsidies are paid by the microgrid
- all benefits are allocated to the microgrid
- all inefficiencies are allocated to the microgrd
- 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

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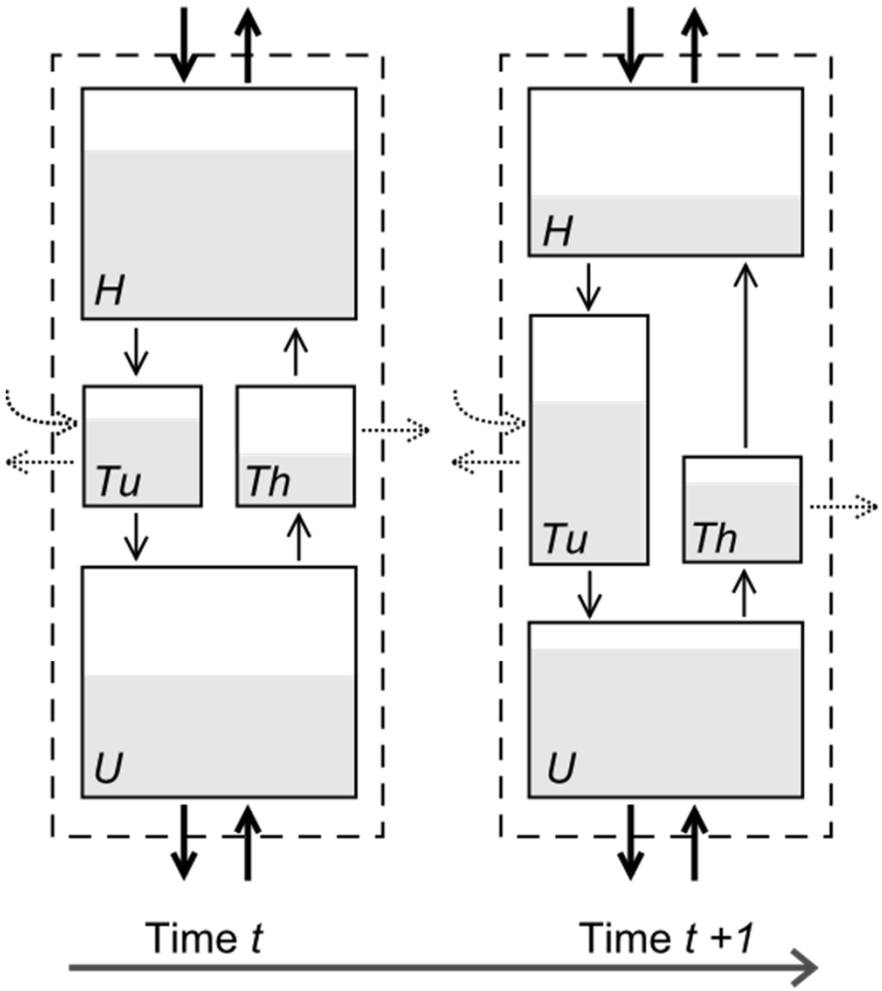


total EV fleet dimension

fleet share in state *i*, time *t*

electricity stored in state *i*, time *t*

electricity transf. between states

electricity I/O in state *i*, time *t*

electricity spent driving in state *i*, time *t*

electricity input for driving in state *i*, time *t*

Possible states, $i = \{H, Tu, Th, U\}$
H - Home
Tu - In Traffic to uGrid
Th - In Traffic to Home
U - uGrid

# EV fleet aggregator

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**Parameters**

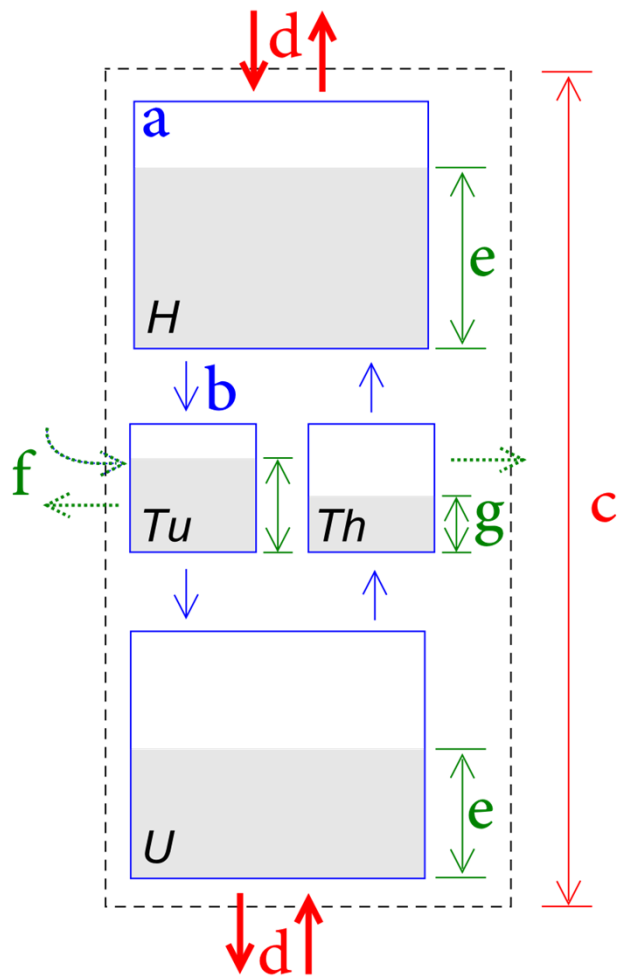
a) fleet distribution
b) fleet transitions

**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

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- 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

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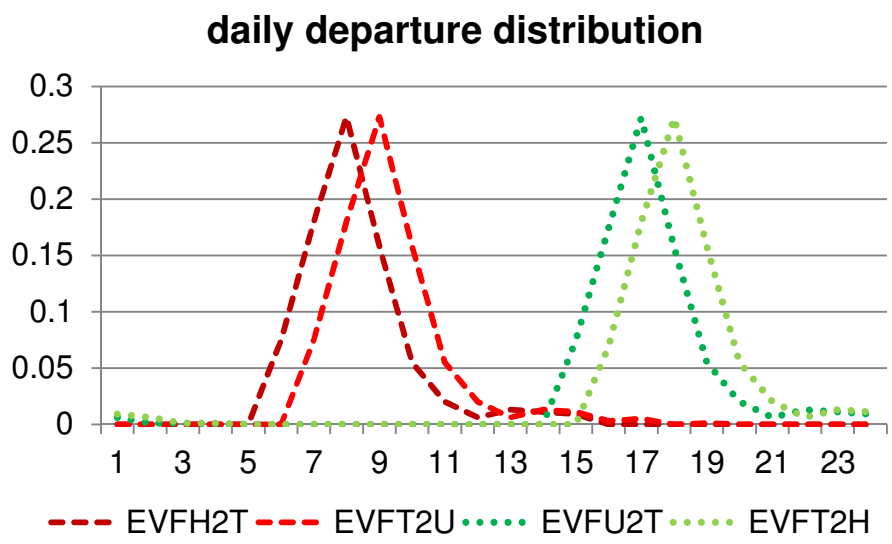
EV fleet distribution obtained from a 2009 US survey on departure times for daily commute round trips [1]




[1] *Source*: B. Mckenzie and M. Rapino, "Commuting in the United States : 2009, American Community Survey Reports, ACS-15.," Washington, DC, 2011

# Case study - source of uncertainty

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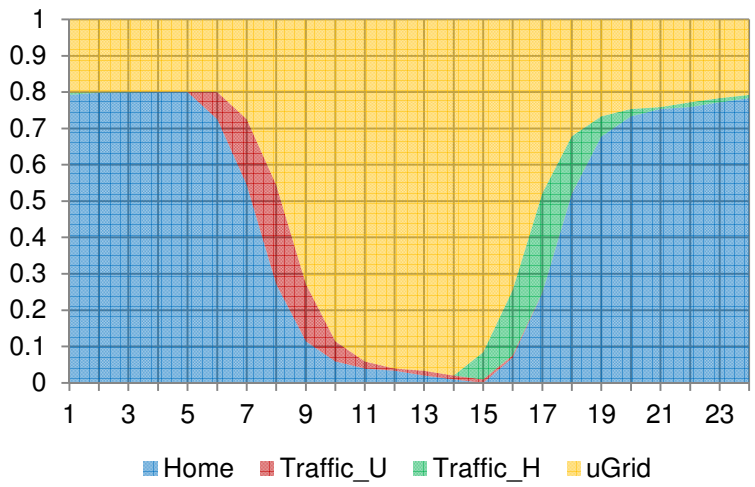
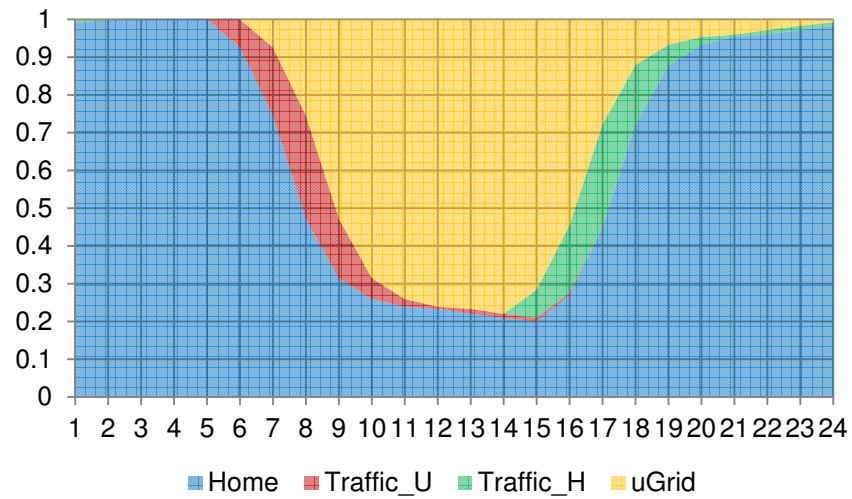
not all cars are considered in the daily departure distribution: driving scenarios obtained by maximizing time at the uGrid (S1), at home (S3), and using the average (S2)

**driving schedule - scenario 1**




**driving schedule - scenario 3**




[1] *Source*: B. Mckenzie and M. Rapino, "Commuting in the United States : 2009, American Community Survey Reports, ACS-15.," Washington, DC, 2011

# Case study - statistics

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

| model options | equations | variables | discrete variables |
|---|---|---|---|
| no investment in DER | 210 926 | 159 035 | 22 186 |
| investment (deterministic) | 324 215 | 272 309 | 50 424 |
| investment (stochastic) | 915 041 | 759 189 | 127 032 |

| run | total energy costs ($) | computation time (s) | iterations | optimality gap |
|---|---|---|---|---|
| BAU | 1 742 812 | 1.837 | 0 | 0.000% |
| NOEVP5 | 1 740 676 | 674.434 | 60730 | 0.000% |
| EVS1P5 | 1 588 059 | 1243.753 | 114983 | 0.003% |
| EVS2P5 | 1 607 688 | 1344.264 | 111697 | 0.083% |
| EVS3P5 | 1 623 344 | 1602.992 | 131812 | 0.068% |
| EVSTP5 | 1 607 547 | 11394.901 | 492815 | 0.091% |
| NOEVP12 | 1 608 008 | 296.32 | 87708 | 0.014% |
| EVS1P12 | 1 556 444 | 2195.054 | 188280 | 0.062% |
| EVS2P12 | 1 578 892 | 1798.088 | 167902 | 0.092% |
| EVS3P12 | 1 590 345 | 3771.245 | 194991 | 0.100% |
| EVSTP12 | 1 581 937 | 36069.462 | 1119387 | 0.190% |

*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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| run | total energy costs (k$) | total $CO_2$ (t $CO_2$) | adopted capacity (kW) | | | | |
|---|---|---|---|---|---|---|---|
| | | | PV | ST | ICE HX | ES | EV |
| BAU | 1 743 | 6 444 | - | - | - | - | - |
| NOEVP5 | 1 741 | 6 424 | 0 | 73 | 0 | 166 | - |
| EVS1P5 | 1 588 | 4 658 | 58 | 0 | 250 | 0 | 25650 |
| EVS2P5 | 1 608 | 4 621 | 0 | 17 | 250 | 0 | 25650 |
| EVS3P5 | 1 623 | 4 902 | 0 | 15 | 250 | 0 | 18242 |
| EVSTP5 | 1 608 | 4 637 | 0 | 18 | 250 | 0 | 25650 |

| run | total energy costs (k$) | total $CO_2$ (kg $CO_2$) | adopted capacity (kW) | | | |
|---|---|---|---|---|---|---|
| | | | PV | ICE HX | AC | EV |
| BAU | 1 743 | 6 444 | - | - | - | - |
| NOEVP12 | 1 608 | 4 620 | 1 128 | 750 | 143 | - |
| EVS1P12 | 1 556 | 3 862 | 1 075 | 500 | 0 | 24 897 |
| EVS2P12 | 1 579 | 3 949 | 1 143 | 500 | 63 | 20 695 |
| EVS3P12 | 1 590 | 4 526 | 955 | 750 | 121 | 5 312 |
| EVSTP12 | 1 582 | 4 250 | 970 | 750 | 120 | 12 506 |

# Case study – key results

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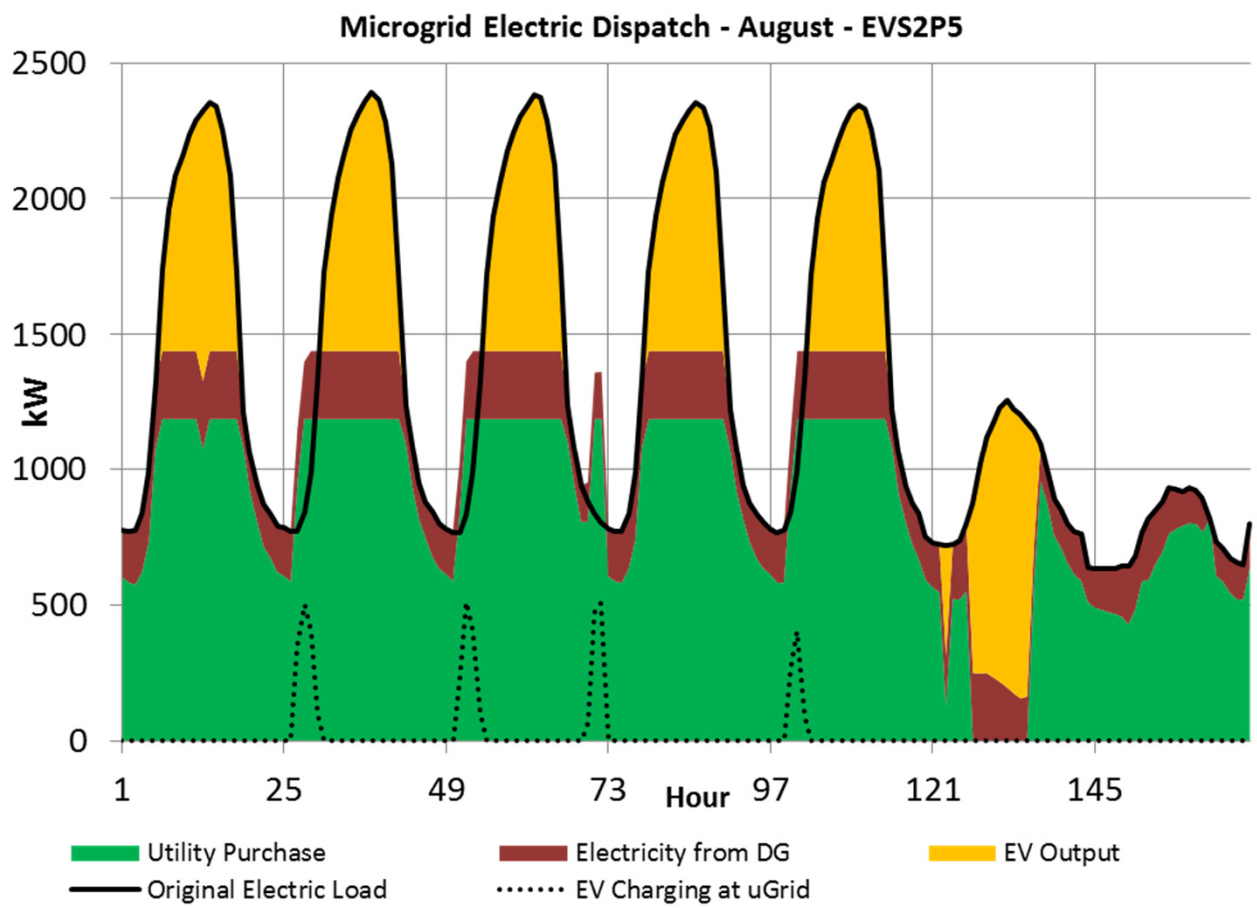


- EVs are used during the day when electricity prices are highest
- optimal scheduling behavior includes using the EV batteries for load shifting
- utility purchase is kept mostly flat, avoiding high power demand charges
- ICE adopted are also used to charge the EV batteries (increases capacity factors)

# Effect of uncertainty in dispatch

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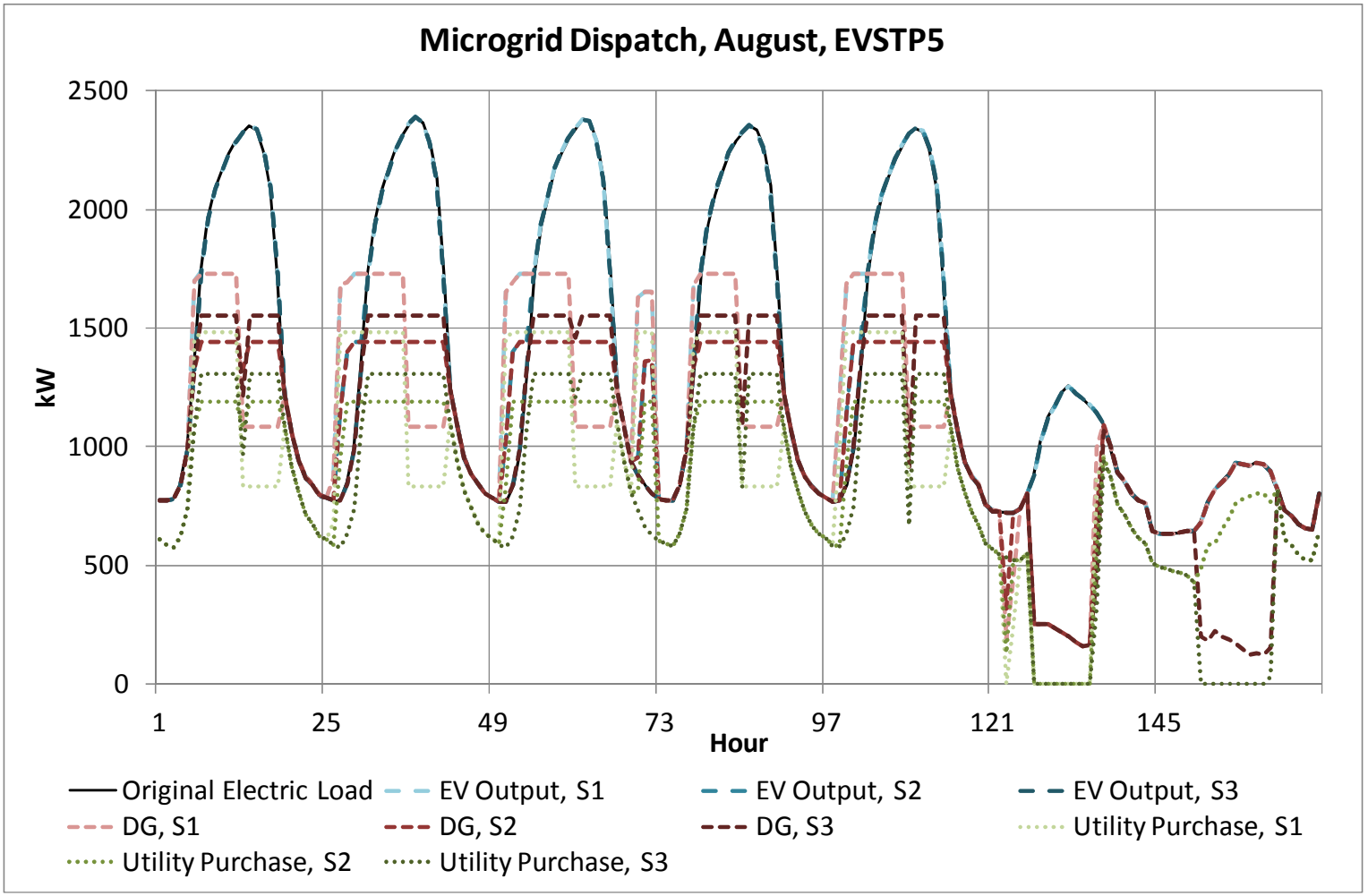

# Case study – key results

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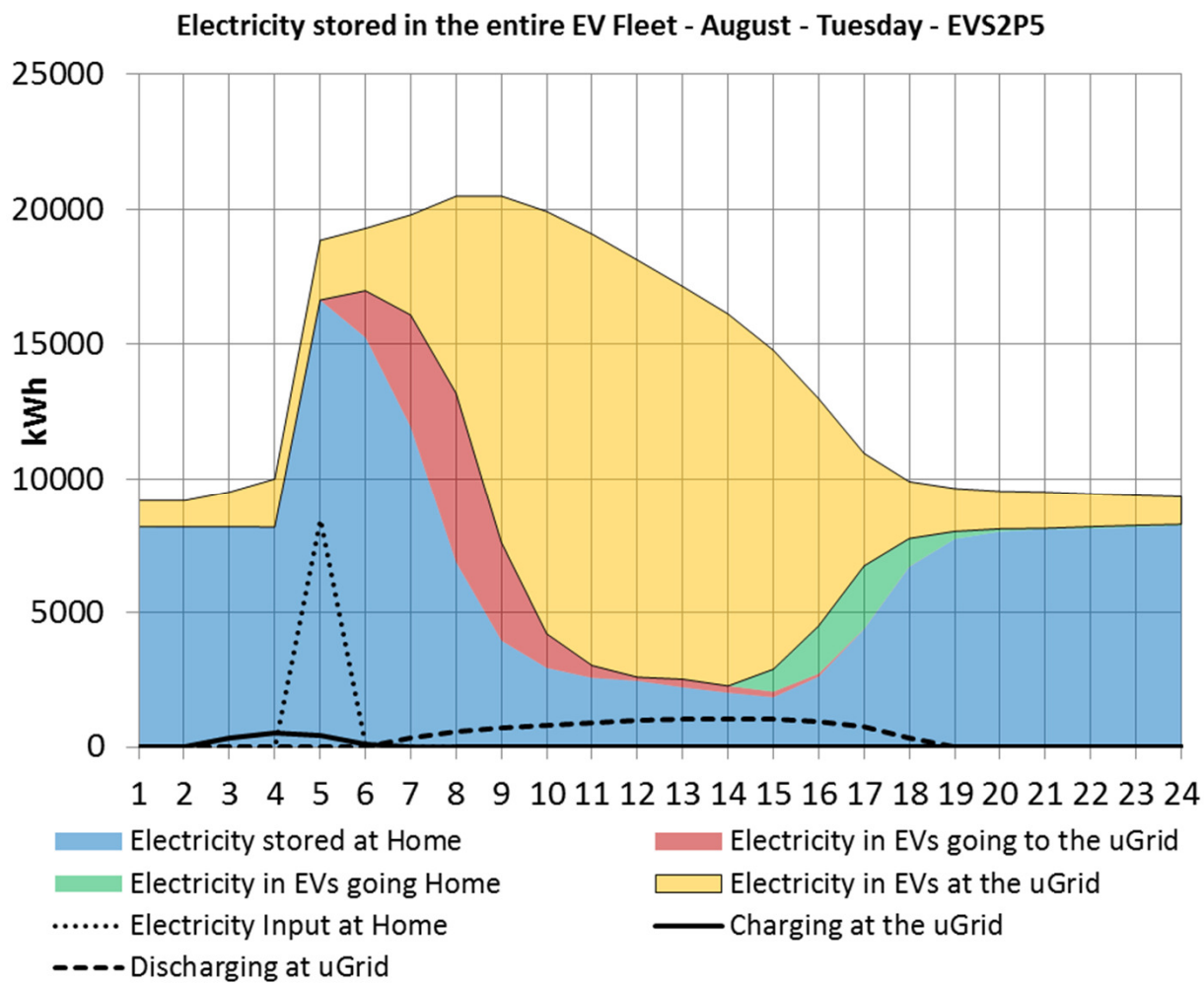


- charge batteries at home and use the electricity at the microgrid throughout the day
  (home charging rate: 6c/kWh, microgrid: >> 10c/kWh)
- charging occurs in early morning hours, both at home and at the microgrid

# Case study – key results

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- the introduction of EVs leads to financial savings and $CO_2$ 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

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- 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

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# DER-CAM

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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 $CO_2$, ...

**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, $CO_2$ emissions, …

# EV fleet aggregator

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$$EVFH_{\omega,m,t,h} = EVFH_{\omega,m,t,h-1} + EVFT2H_{\omega,m,t,h} - EVFH2T_{\omega,m,t,h}$$

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

$$EVFTU_{\omega,m,t,h} = EVFTU_{\omega,m,t,h-1} + EVFH2T_{\omega,m,t,h} - EVFT2U_{\omega,m,t,h}$$

$$EVFTH_{\omega,m,t,h} = EVFTH_{\omega,m,t,h-1} + EVFU2T_{\omega,m,t,h} - EVFT2H_{\omega,m,t,h}$$

$$EVFU_{\omega,m,t,h} = EVFU_{\omega,m,t,h-1} + EVFT2U_{\omega,m,t,h} - EVFU2T_{\omega,m,t,h}$$

<u>States</u>

| | |
|---|---|
| $EVFH_{\omega,m,t,h}$ | share of total fleet at home in scenario w, 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.. |

<u>Transitions</u>

| | |
|---|---|
| $EVFH2T_{\omega,m,t,h}$ | share of total fleet that goes from home to traffic in scenario w, 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... |

# EV fleet aggregator

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- **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

$$esevh_{\omega,m,t,h} =$$
$$= \left( esevh_{\omega,m,t,h-1} \cdot \left(1 - \frac{\mathrm{EVFH2T}_{\omega,m,t,h}}{\mathrm{EVFH}_{\omega,m,t,h-1}}\right) + esevth_{\omega,m,t,h-1} \cdot \frac{\mathrm{EVFT2H}_{\omega,m,t,h}}{\mathrm{EVFTH}_{\omega,m,t,h-1}}\right) \cdot (1 - \varphi_k) +$$
$$+ eievh_{\omega,m,t,h} - eoevh_{\omega,m,t,h}$$

- **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

$$esevtu_{\omega,m,t,h} =$$
$$= \left( esevtu_{\omega,m,t,h-1} \cdot \left(1 - \frac{\mathrm{EVFT2U}_{\omega,m,t,h}}{\mathrm{EVFTU}_{\omega,m,t,h-1}}\right) + esevh_{\omega,m,t,h-1} \cdot \frac{\mathrm{EVFH2T}_{\omega,m,t,h}}{\mathrm{EVFH}_{\omega,m,t,h-1}}\right) \cdot (1 - \varphi_k) +$$
$$+ \left( \sum_h \left(\mathrm{EVFTU}_{\omega,m,t,h} + \mathrm{EVFTH}_{\omega,m,t,h}\right) \cdot \frac{\mathrm{EVFH2T}_{\omega,m,t,h}}{\sum_h \mathrm{EVFH2T}_{\omega,m,t,h}} - \mathrm{EVFT2U} \right) \cdot \frac{cap_k}{\mathrm{EVBat}} \cdot \mathrm{EVDC}$$

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