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Title

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

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

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Outline

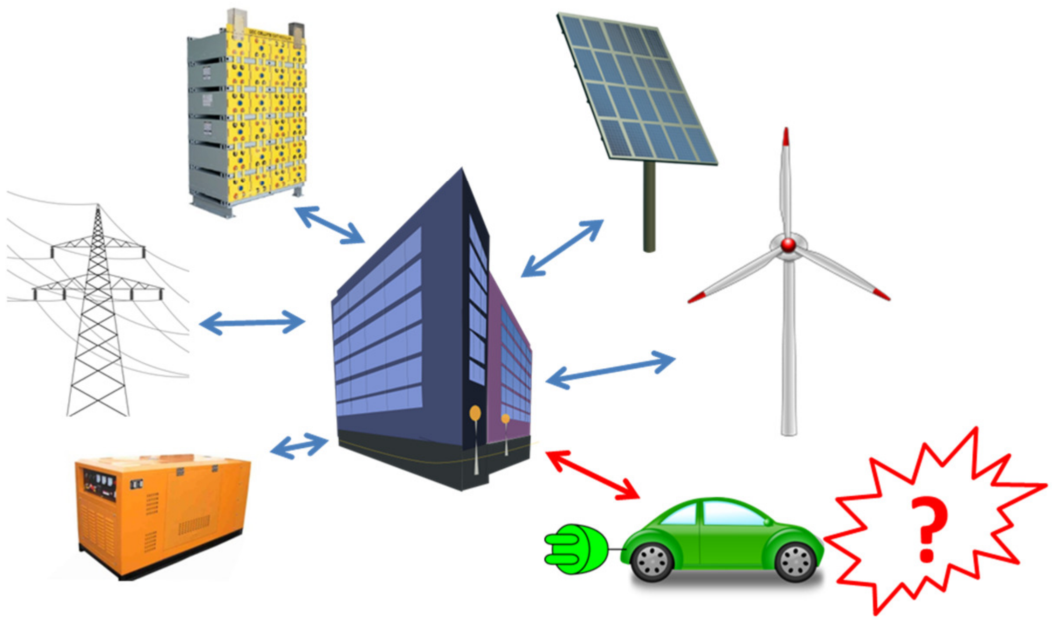
- Motivation
- The Distributed Energy Resources Customer Adoption Model (DER-CAM)
- DER-CAM stochastic formulation
- EV fleet aggregator
- Case study
- Results
- Conclusions and next steps

Motivation

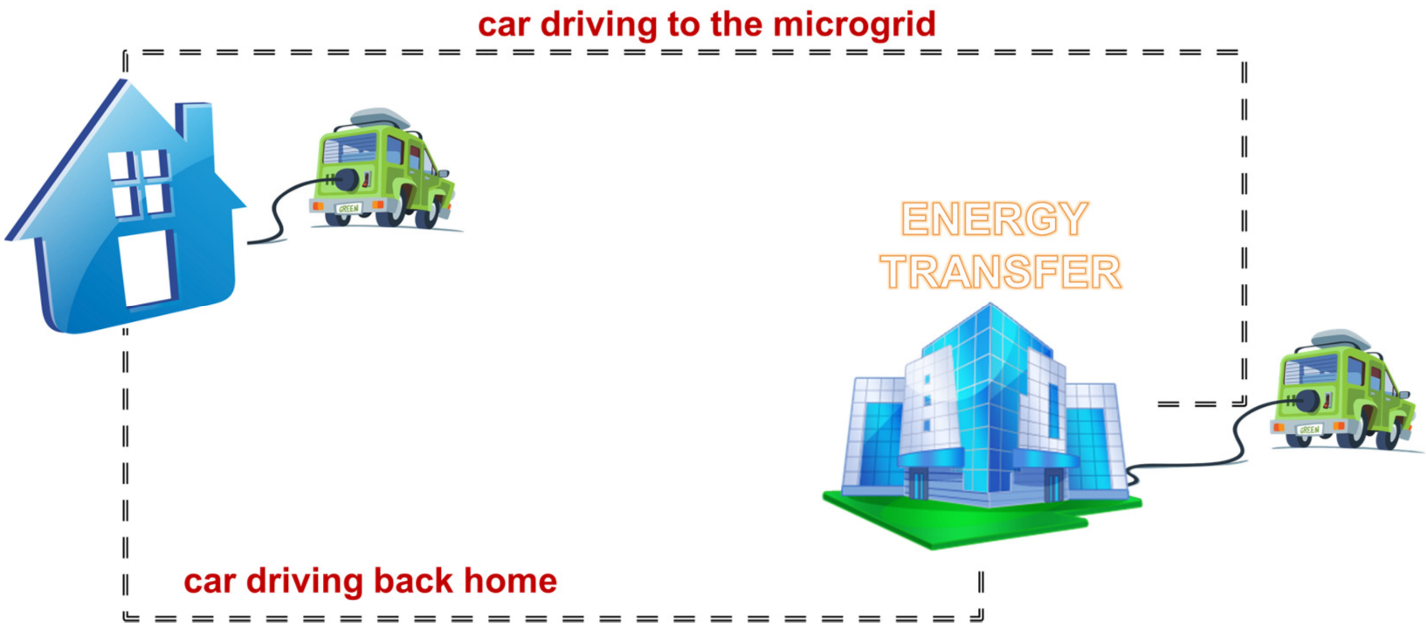
Increasing penetration of electric vehicles (EVs) creates **DER** potential

⇩

Impact on optimal DER investment decisions

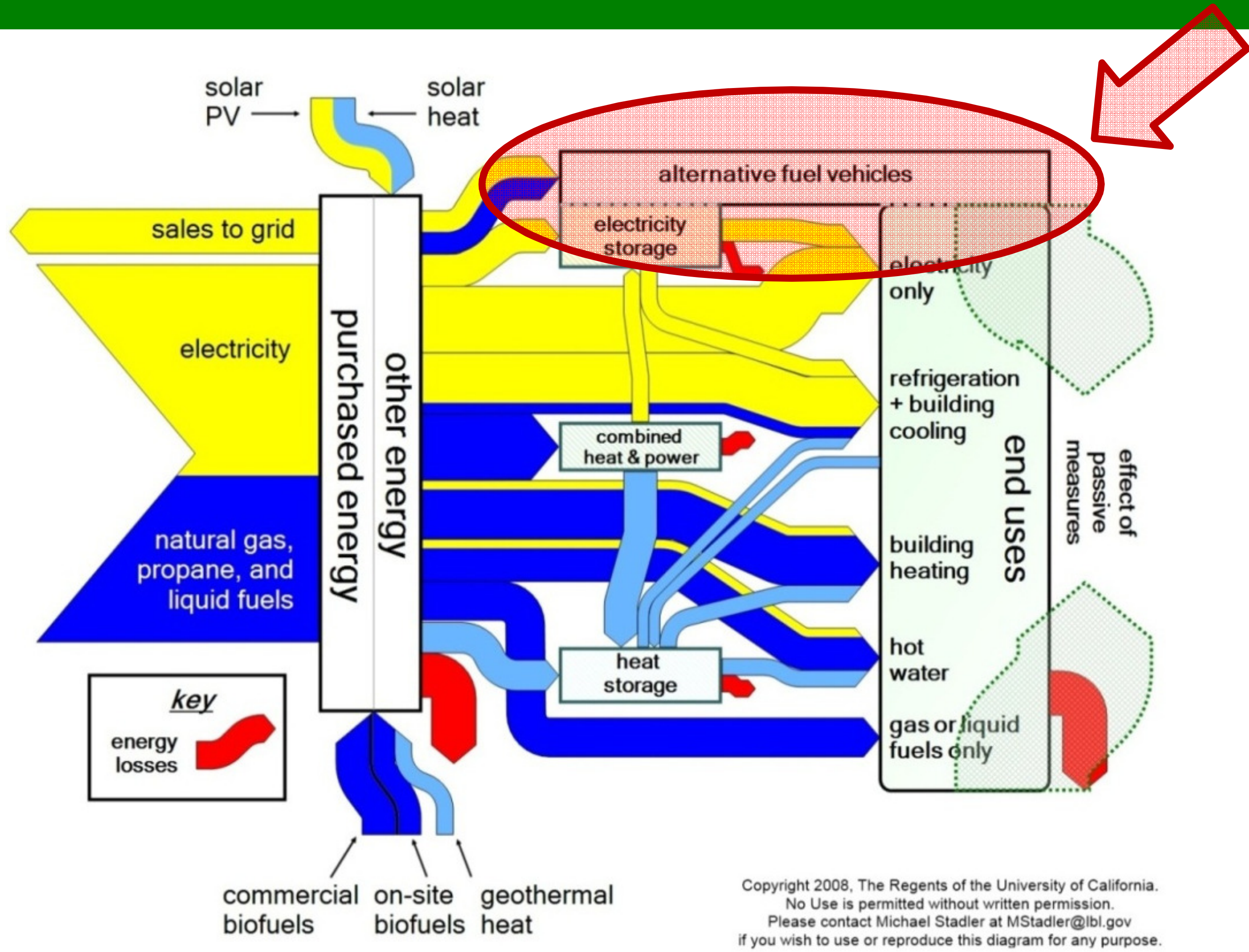


Motivation



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

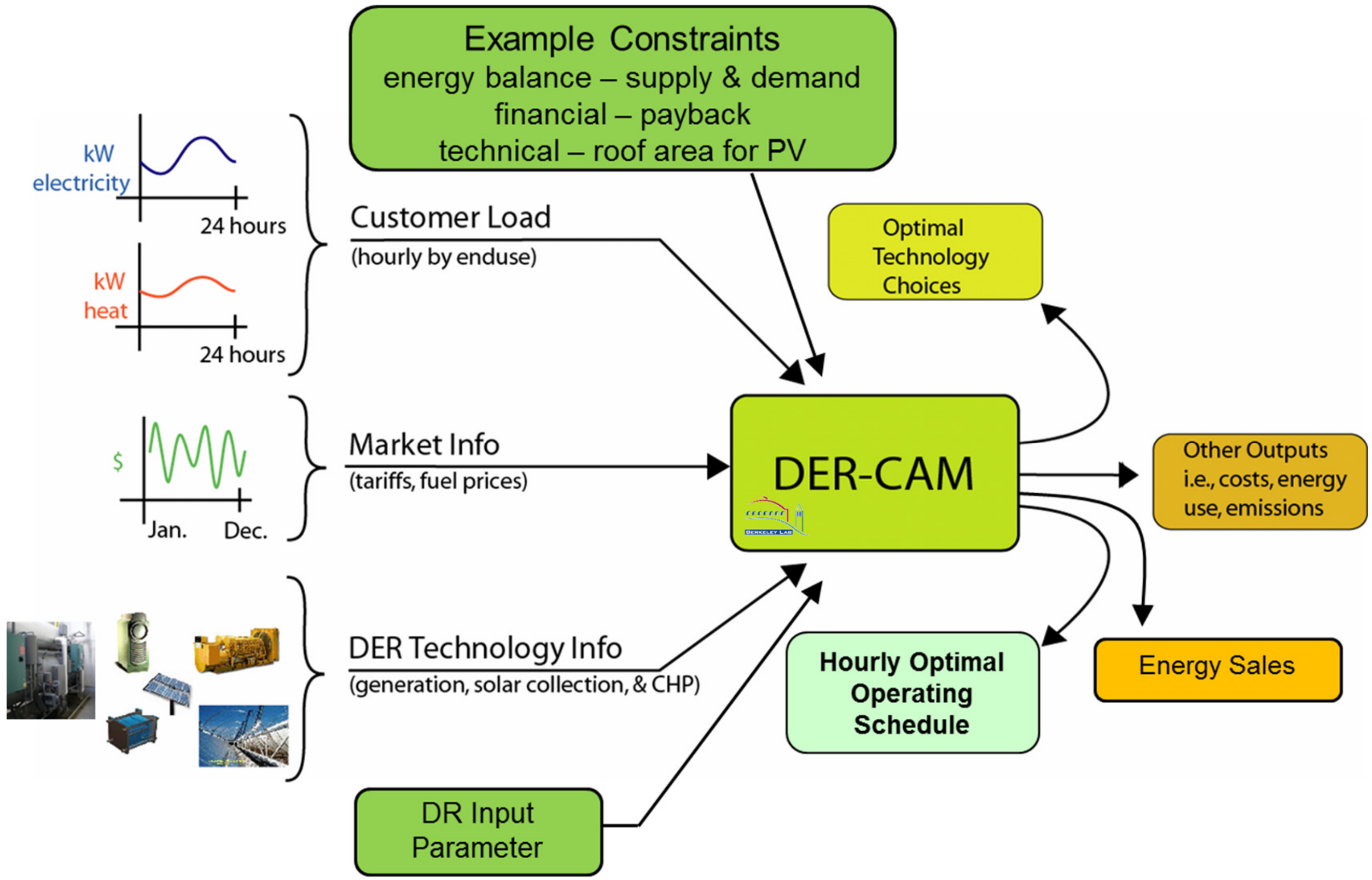
Motivation: the microgrid / energy flow



DER-CAM

- 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



Example Constraints
energy balance – supply & demand
financial – payback
technical – roof area for PV
kW
electricity
24 hours
kW
heat
24 hours
Customer Load
(hourly by enduse)
$
Jan.
Dec.
Market Info
(tariffs, fuel prices)
DER Technology Info
(generation, solar collection, & CHP)
DR Input
Parameter
DER-CAM
Optimal
Technology
Choices
Other Outputs
i.e., costs, energy
use, emissions
Hourly Optimal
Operating
Schedule
Energy Sales

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_ω	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

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 ω; 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

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

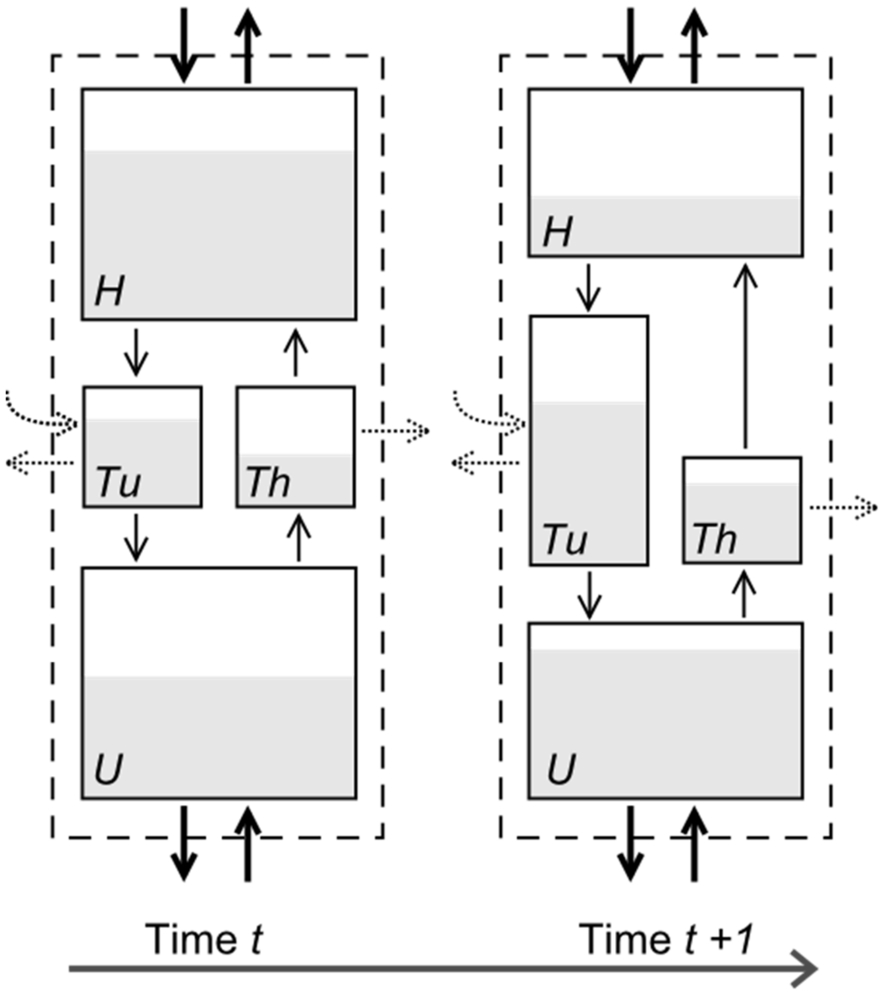
pEV	electricity price at Home
η_c	EV battery charging efficiency
η_{dc}	EV battery discharging efficiency

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 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



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

Parameters

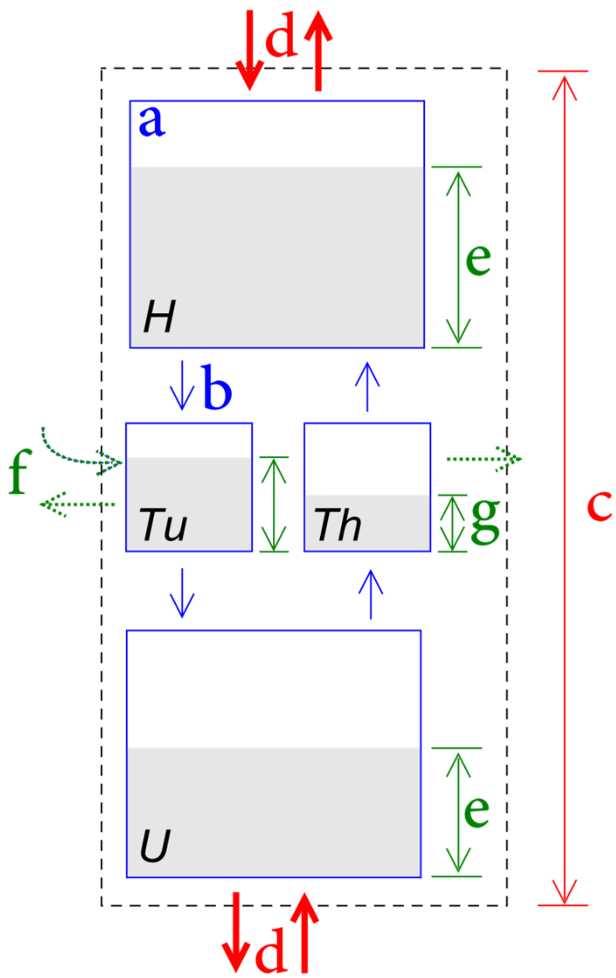
a) fleet distribution
b) fleet transitions

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

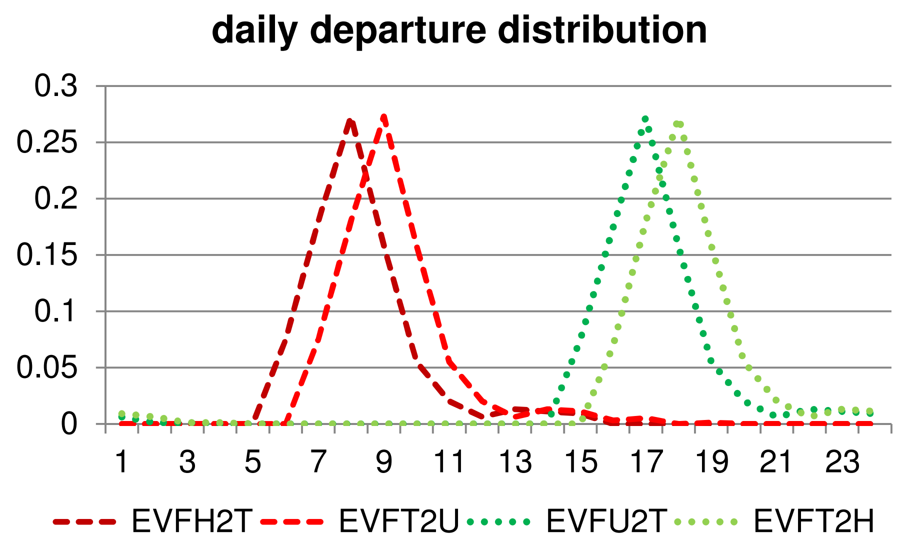
Possible technologies
internal combustion engines, micro-turbines, gas turbines, fuel cells, heat exchangers, PV, solar thermal, absorption chillers, stationary electric storage, and electric vehicles

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

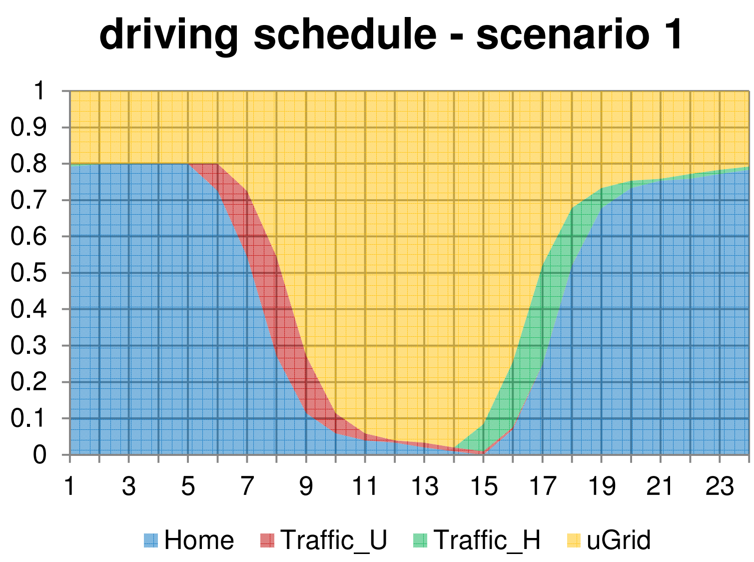
EV fleet distribution obtained from a 2009 US survey on departure times for daily commute round trips [1]

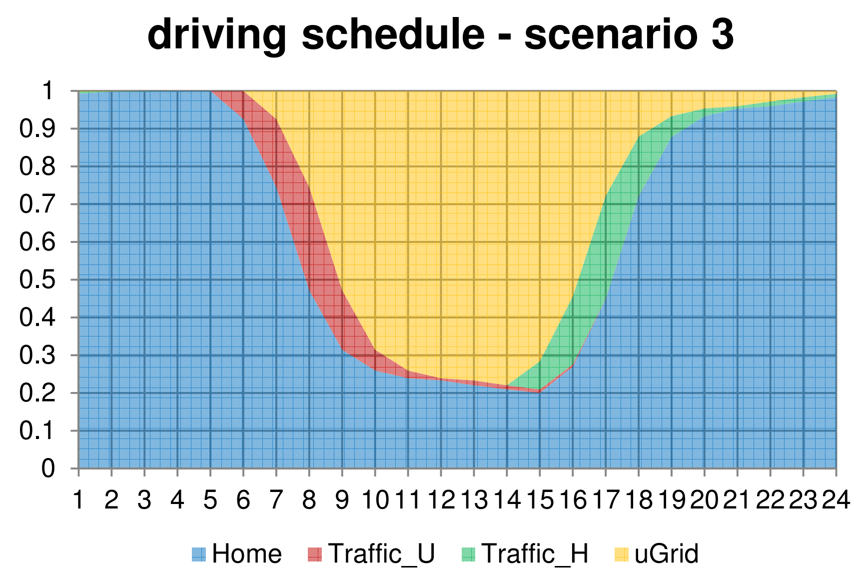


[1] *Source*: B. Mckenzie and M. Rapino, "Commuting in the United States : 2009, American Community Survey Reports, ACS-15.," Washington, DC, 2011

Case study - source of uncertainty

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)





[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

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%

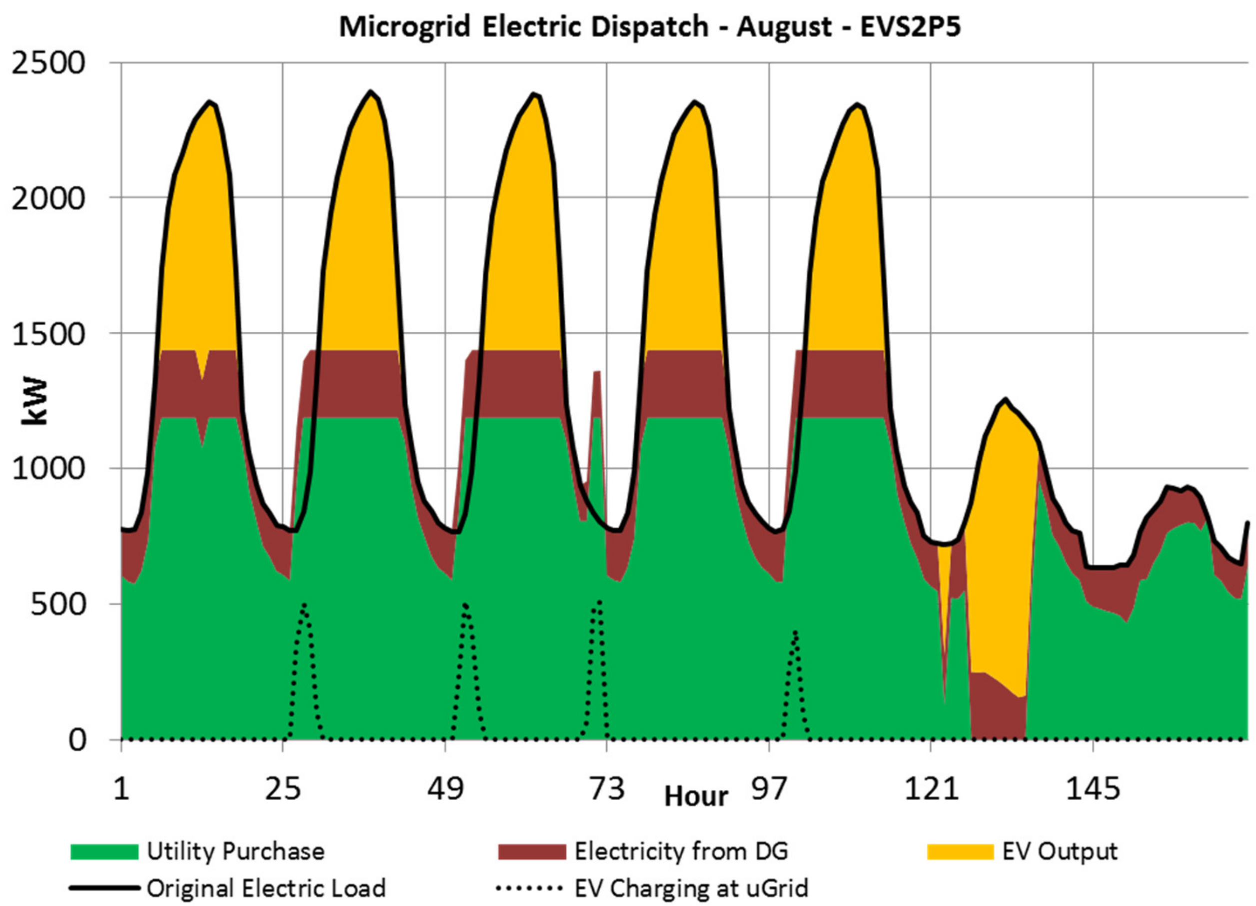
BAU – no investments; NOEV – invest without EVs; EV – invest in EV infrastructure; S1/S2/S3 – fleet distribution scenario; ST – stochastic mode; P5/P12 – maximum payback

Case study – key results

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

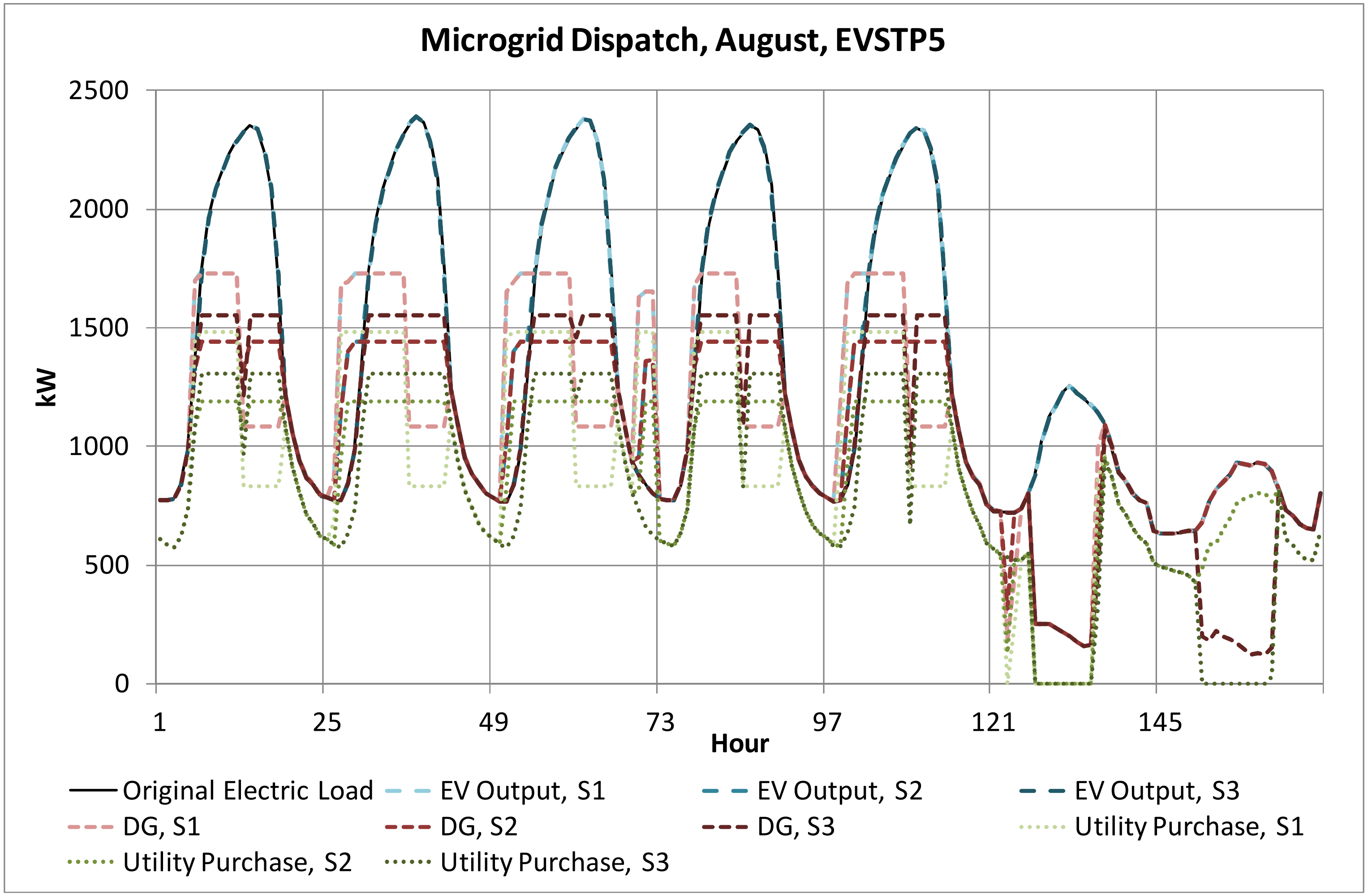
run	total energy costs (k$)	total CO_2 (kg CO_2)	adopted capacity (kW)			
			PV	ICE HX	AC	EV
BAU	1 743	6 444	-	-	-	-
NOEVP12	1 608	4 620	1 128	750	143	-
EVS1P12	1 556	3 862	1 075	500	0	24 897
EVS2P12	1 579	3 949	1 143	500	63	20 695
EVS3P12	1 590	4 526	955	750	121	5 312
EVSTP12	1 582	4 250	970	750	120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

Case study – key results

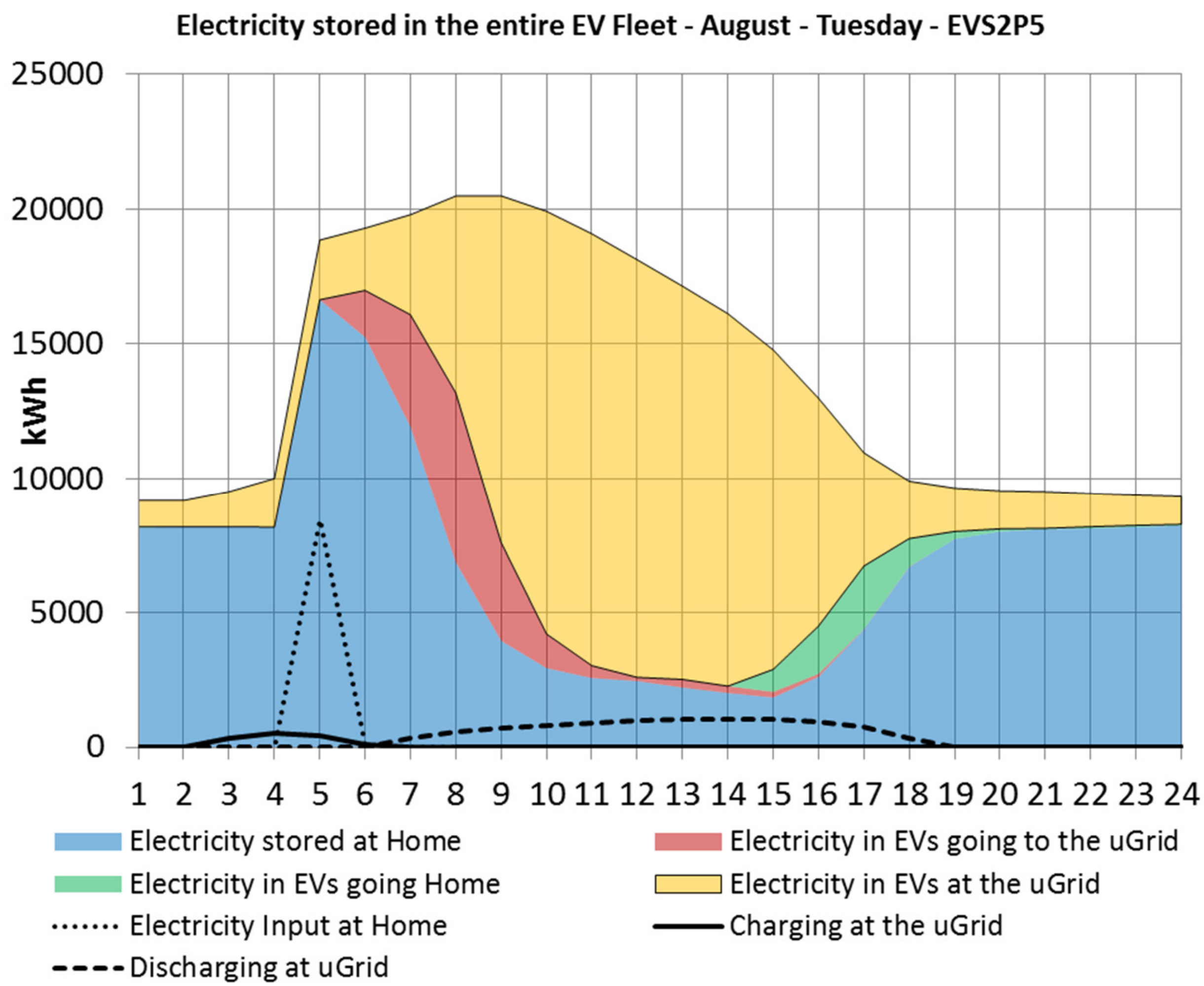


- EVs are used during the day when electricity prices are highest
- optimal scheduling behavior includes using the EV batteries for load shifting
- utility purchase is kept mostly flat, avoiding high power demand charges
- ICE adopted are also used to charge the EV batteries (increases capacity factors)

Effect of uncertainty in dispatch



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 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

- 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

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

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

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

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

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

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

States

$EVFH_{\omega,m,t,h}$	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..

Transitions

$EVFH2T_{\omega,m,t,h}$	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

- **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

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

- **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

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

DISCLAIMER