Economic and Environmental Optimization of Microgrids*)

*) This work is partly financed by the US Department of Energy, Office of Electricity Delivery & Energy Reliability (OE)

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August 2014

DER-CAM DECISION SUPPORT TOOL FOR DECENTRALIZED ENERGY SYSTEMS
ANALYTICS | PLANNING | OPERATIONS

Team: G. Cardoso, N. DeForest, W. Feng, D. Baldassari, T. Brandt, N. DeForest, J. Eto, L. Le Gall, G. Gehbauer, M. Hartner, S. Mashayekh, C. Marnay, C. Milan, J. Reilly, M. Stadler, D. Steen, J. Tjaeder, N. Zhou

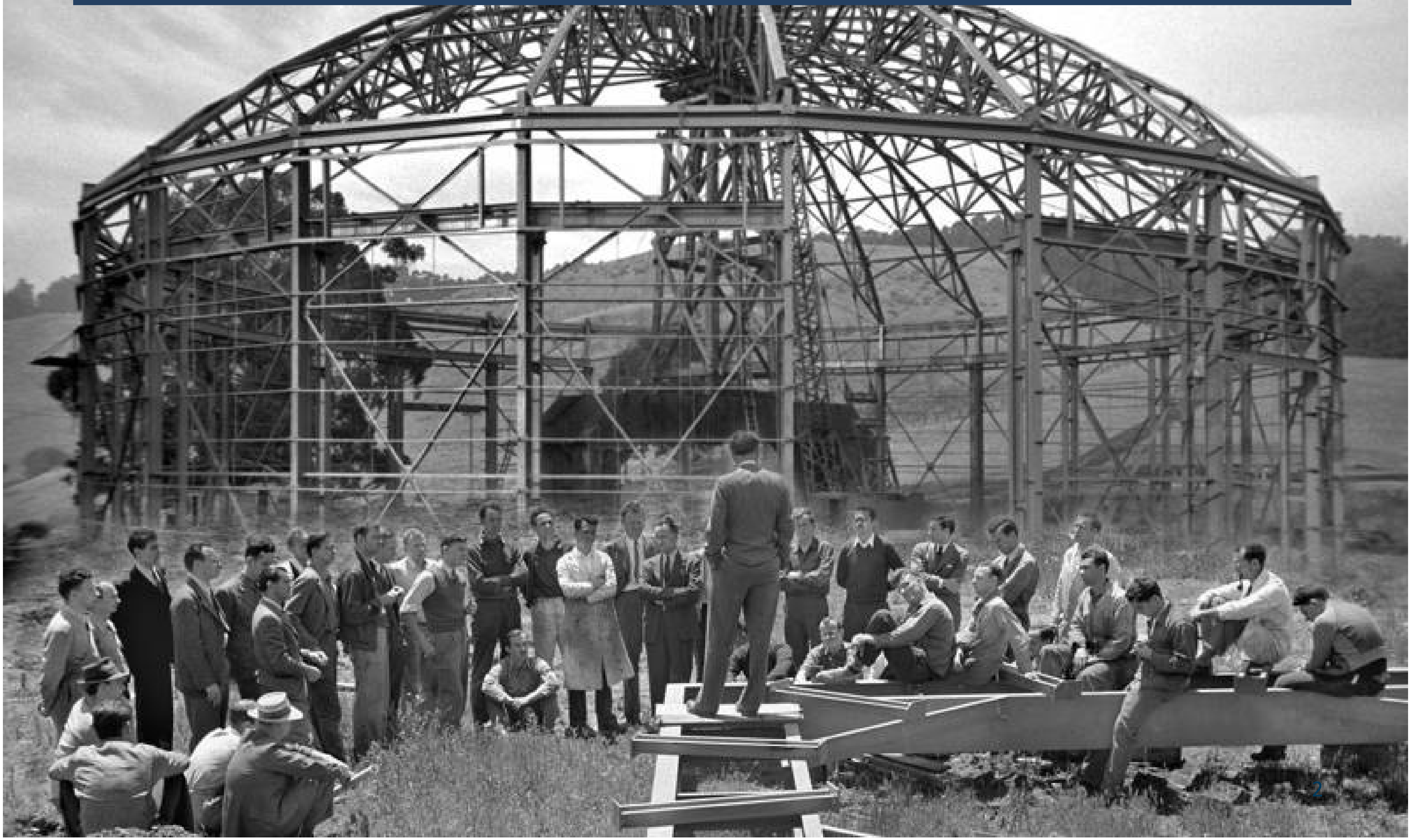
Partners: Universidad Pontificia Comillas - IIT, Massachusett Institute of Technology (MIT), MIT Lincoln Laboratory, University of New Mexico, CSIRO, TriTechnic, Xcogen Energy, LLC, Public Service New Mexico, NEC, Fort Hunter Liggett

BERKELEY LAB
Lawrence Berkeley National Laboratory

DEPARTMENT OF ENERGY · UNITED STATES OF AMERICA

Lawrence Introduces Big Team Science

Berkeley Laboratory: the first U.S. Department of Energy National Laboratory



13 Nobel Prizes


Luis W. Alvarez


Melvin Calvin

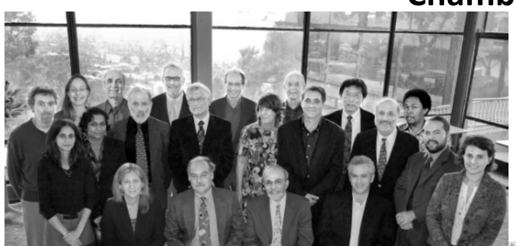

Owen Chamberlain


Steven Chu

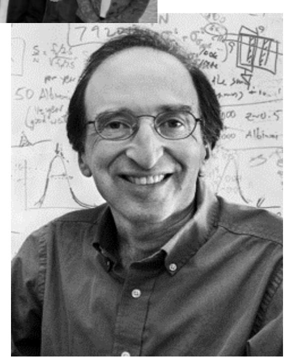

Donald A. Glaser


Ernest Orlando Lawrence


Yuan T. Lee


Intergovernmental Panel on Climate Change (IPCC)


Edwin M. McMillan


Saul Perlmutter


Glenn T. Seaborg


Emilio G. Segrè

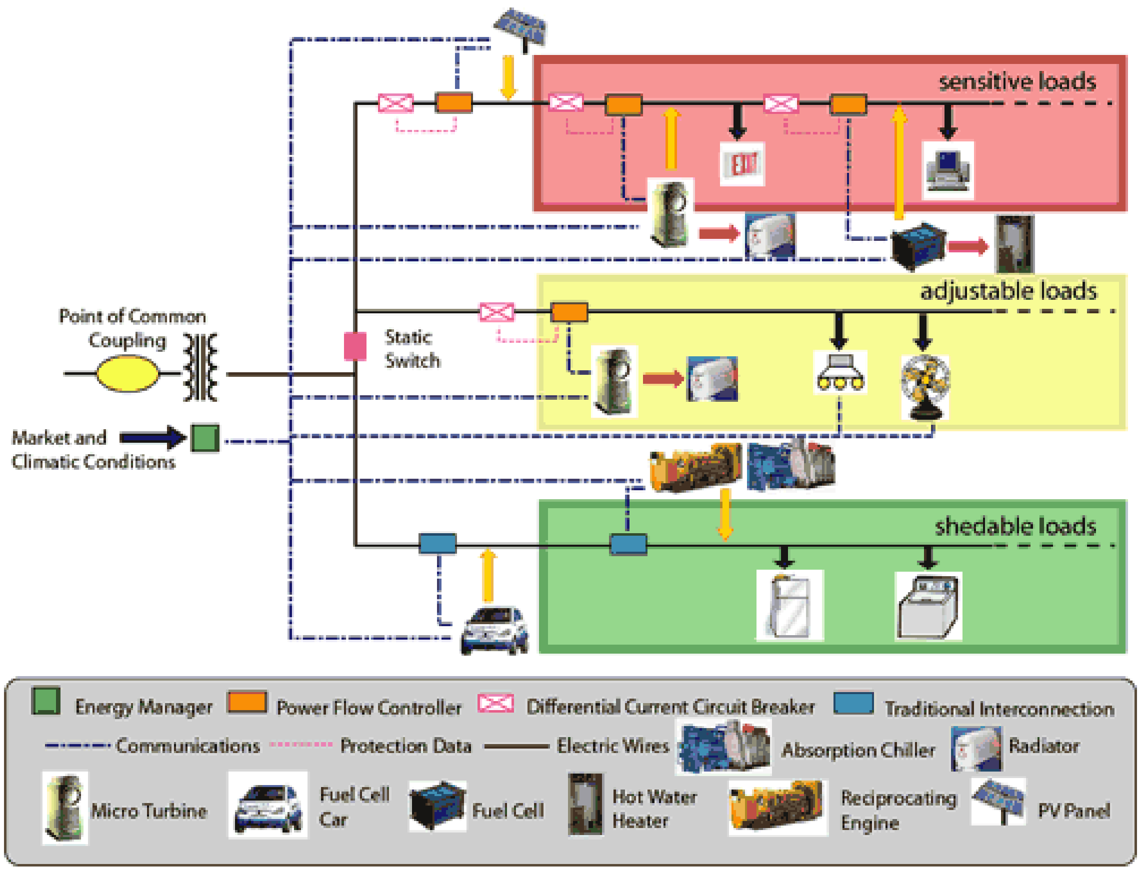

George F. Smoot

What is a Microgrid?

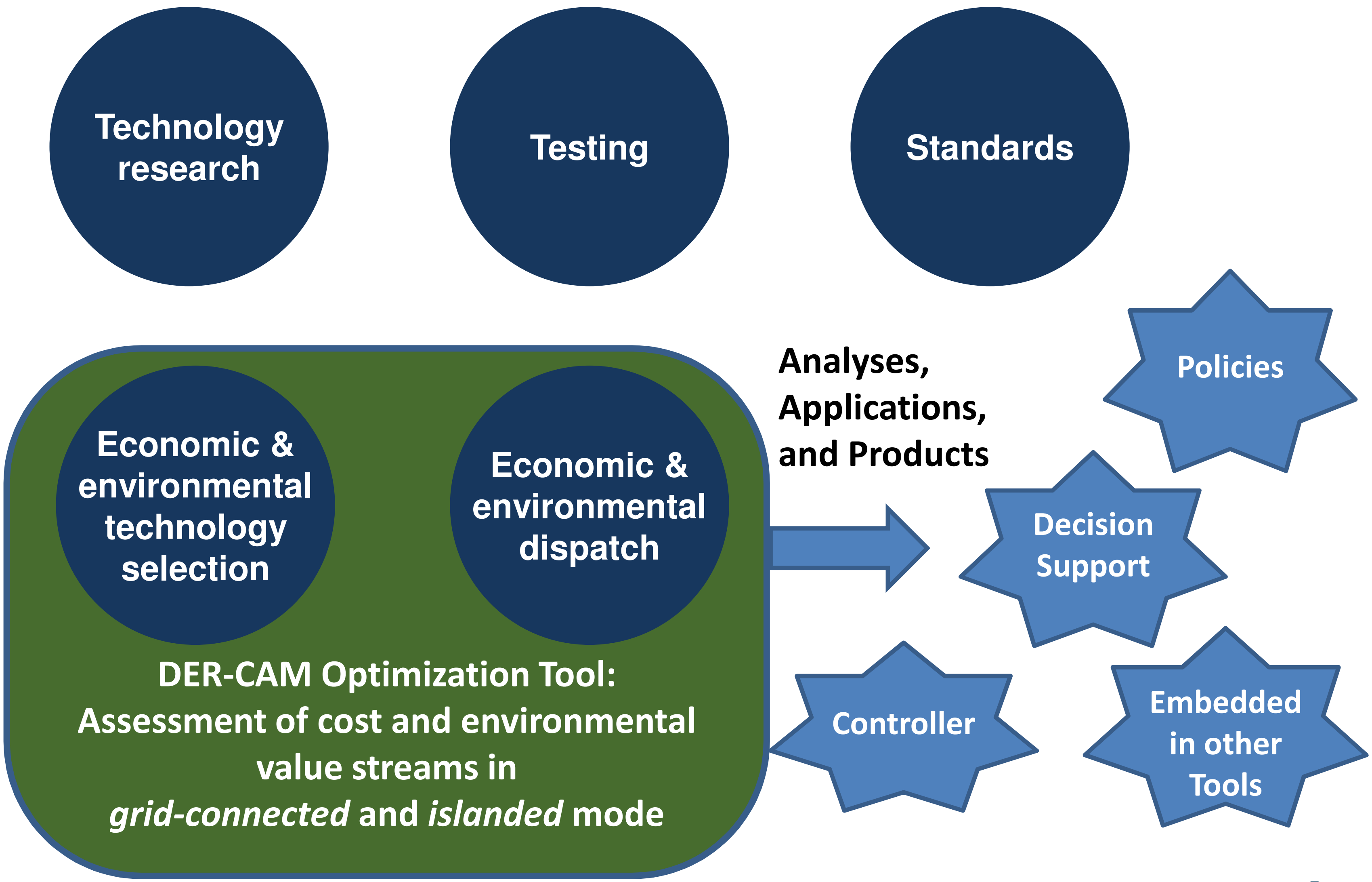
A ***microgrid*** is a

- group of interconnected loads and distributed energy resources
- acts as a single controllable entity with respect to the grid
- can connect/disconnect from the grid
- operates in both grid-connected or island mode

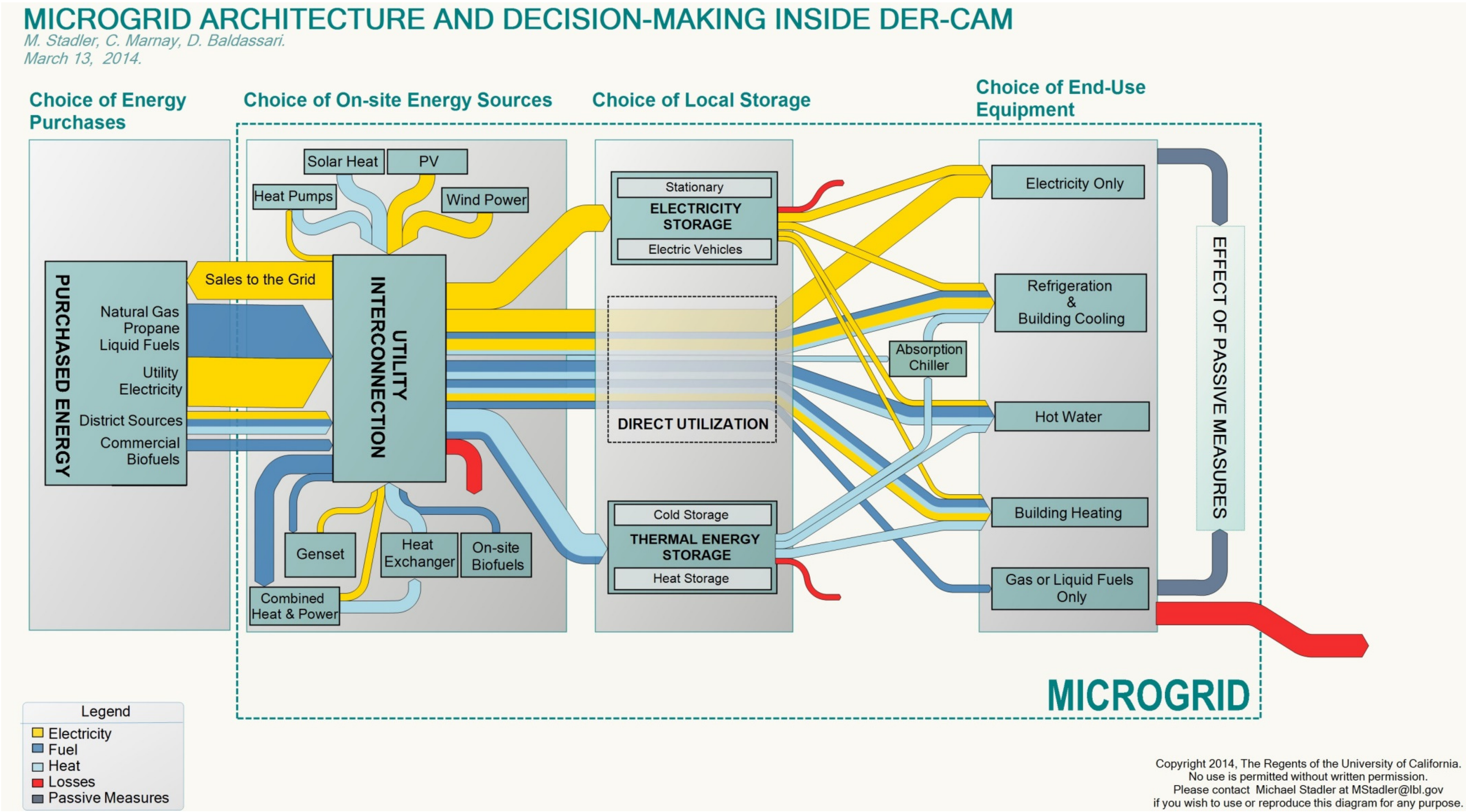
(Microgrid Exchange Group, October 2010)



Our Contribution to Microgrids



Global Model Concept for Microgrids



DER-CAM DECISION SUPPORT TOOL FOR DECENTRALIZED ENERGY SYSTEMS

ANALYTICS | PLANNING | OPERATIONS

Distributed Energy Resources Customer Adoption Model (DER-CAM)

- is a deterministic and stochastic Mixed Integer Linear Program (MILP), written in the General Algebraic Modeling System (GAMS®)
- started as a building CHP optimization tool 13 years ago
- supported by the U.S. DOE, OE, DoD, CEC, private industry
- two main objective functions:
  - cost minimization
  - CO_2 minimization
- other objectives are possible, as well as multi-objective

  subject to microgrid/building constraints and energy balance
- produces optimal investment and dispatch results for biogas/diesel/natural gas CHP, fuel cells, ICE, micro-turbines, gas-turbines; PV, solar thermal, hot and cold water storage, batteries, heat pumps, absorption chiller, EV, passive measures (insulation, window changes, etc..)

DER-CAM DECISION SUPPORT TOOL FOR DECENTRALIZED ENERGY SYSTEMS

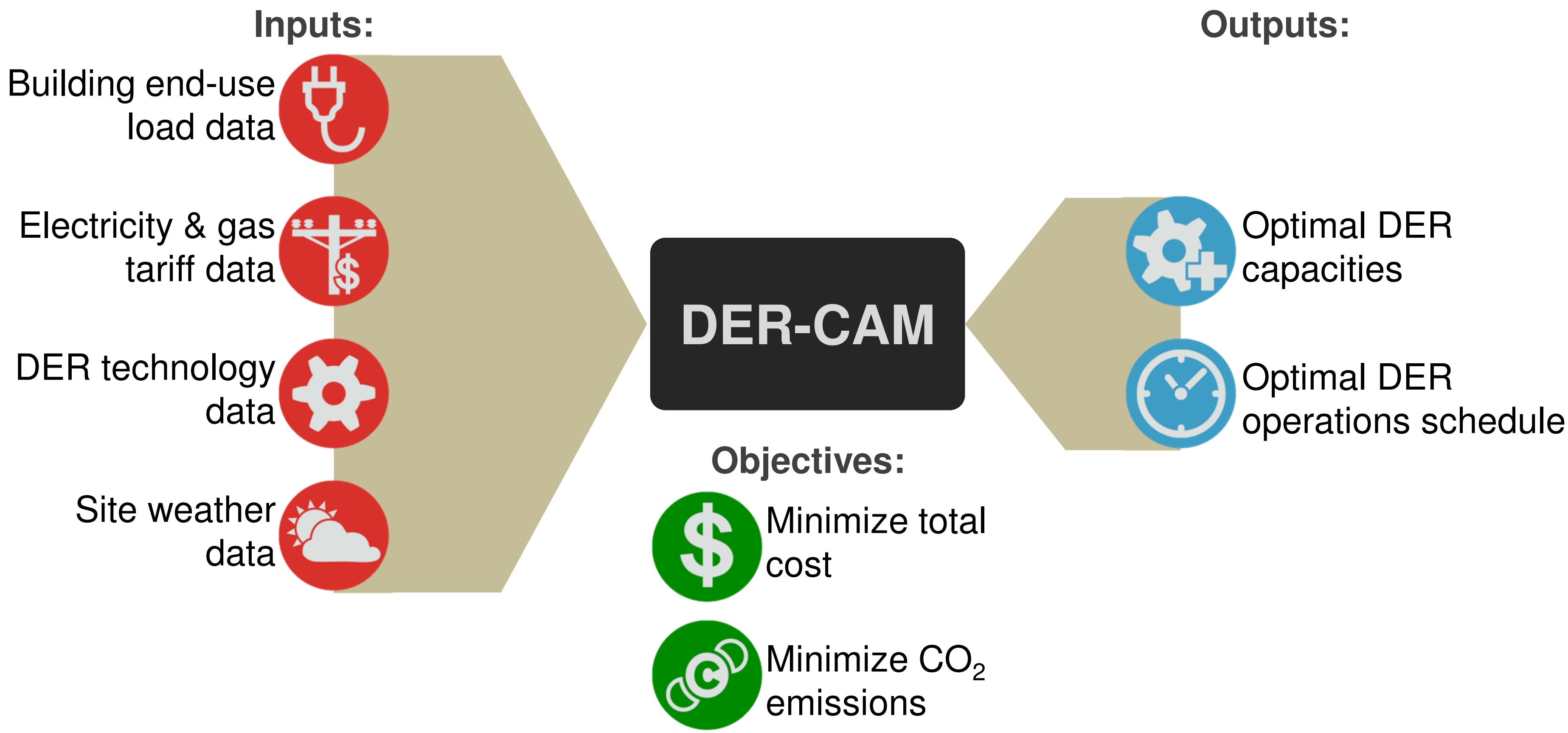
ANALYTICS | PLANNING | OPERATIONS

What is DER-CAM?

- optimizes heating, cooling, electricity, and fuel loads (as natural gas)
- can consider real microgrid conditions as islanding and critical loads
- 17 specific versions exist (http://building-microgrid.lbl.gov/sites/all/files/projects/DER-CAM-Feature-List.pdf)
- commercialization (*web clients*) and predictive controller work under way
- 550 DER-CAM *web clients* to date (English and Chinese version)

DER-CAM DECISION SUPPORT TOOL FOR DECENTRALIZED ENERGY SYSTEMS

ANALYTICS | PLANNING | OPERATIONS



- **Investment & Planning:** determines optimal equipment combination and operation based on *historic* load data, weather, and tariffs
- **Operations:** determines optimal week-ahead scheduling for installed equipment and *forecasted* loads, weather and tariffs

Representative MILP DER-CAM

Simplified* DER-CAM model

Energy balance
+energy purchase
+energy generated onsite
= onsite demand + energy sales

Operational constraints
-generators, chillers, etc. must operate within performance limits
-heat recovered is limited by generated waste heat
-solar radiation / footprint constraint

Objective function, e.g. min. annual energy bill for a test year:
+energy purchase costs
+*amortized* DER technology capital costs
+annual O&M costs
+ CO_2 costs
- energy sales

Financial constraints
-max. allowed payback period, e.g. 12 years

Regulatory constraints
-minimum efficiency requirement
-emission limits
-CO_2 tax
-CA min. eff. requirement for subsidy and feed-in tariff
-ZNEB

Storage and DR constraints
-electricity stored is limited by battery size
-heat storage is limited by reservoir size
-max. efficiency potential for heating and electricity

***does not show all constraints**

DER-CAM

DECISION SUPPORT TOOL FOR DECENTRALIZED ENERGY SYSTEMS

ANALYTICS | PLANNING | OPERATIONS

Our Partners and DER-CAM Licensees

Our Partners

Features and Applications

- remote access
- microgrid capabilities and resilience at Fort Hunter Liggett
- optimization of cooling equipment at UNM
- battery scheduling at Santa Rita Jail

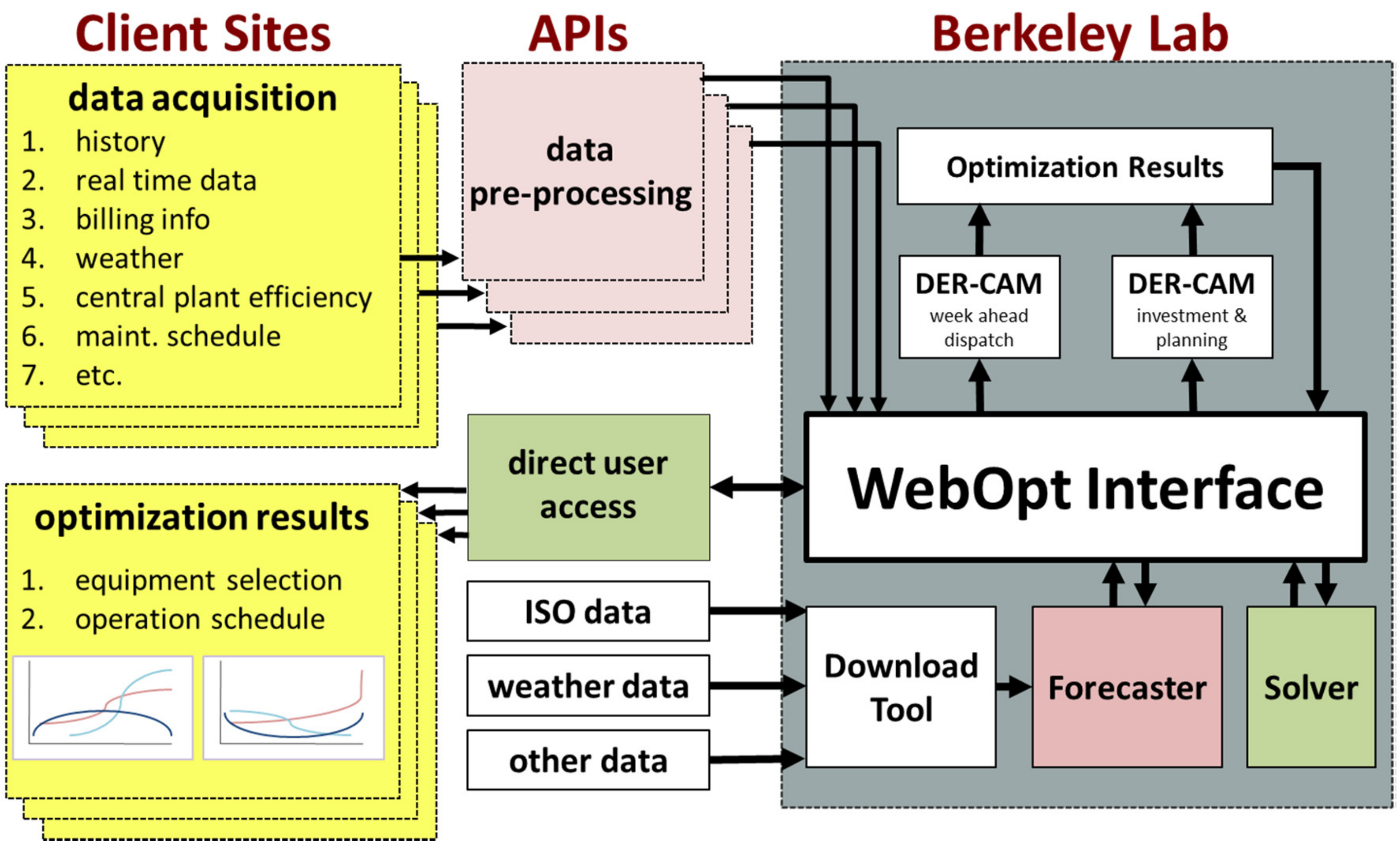
--------------------Backup--

- passive measures
- critical loads
- stepwise approximation of non-linear efficiency curves
- tracking of thermal storage temperature
- wind in DER-CAM
- electrochromic windows
- multi-year optimization (decision support)
- EV modelling
- CA CHP study
- microgrid controller at Fort Hunter Liggett

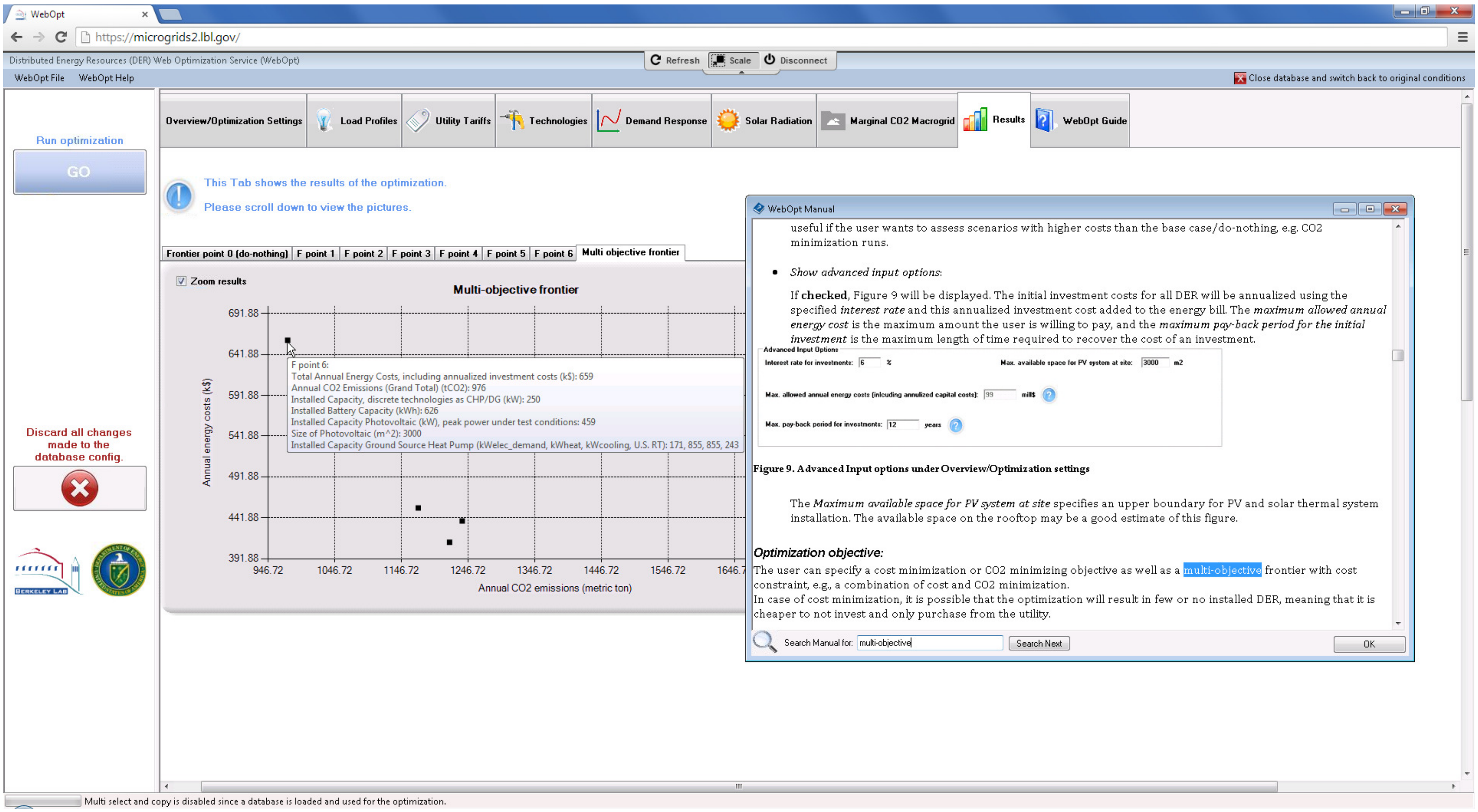
Feature

Remote Access to DER-CAM

Access to DER-CAM via SaaS



Simplified DER-CAM Web-Service for Investment/Planning DER-CAM

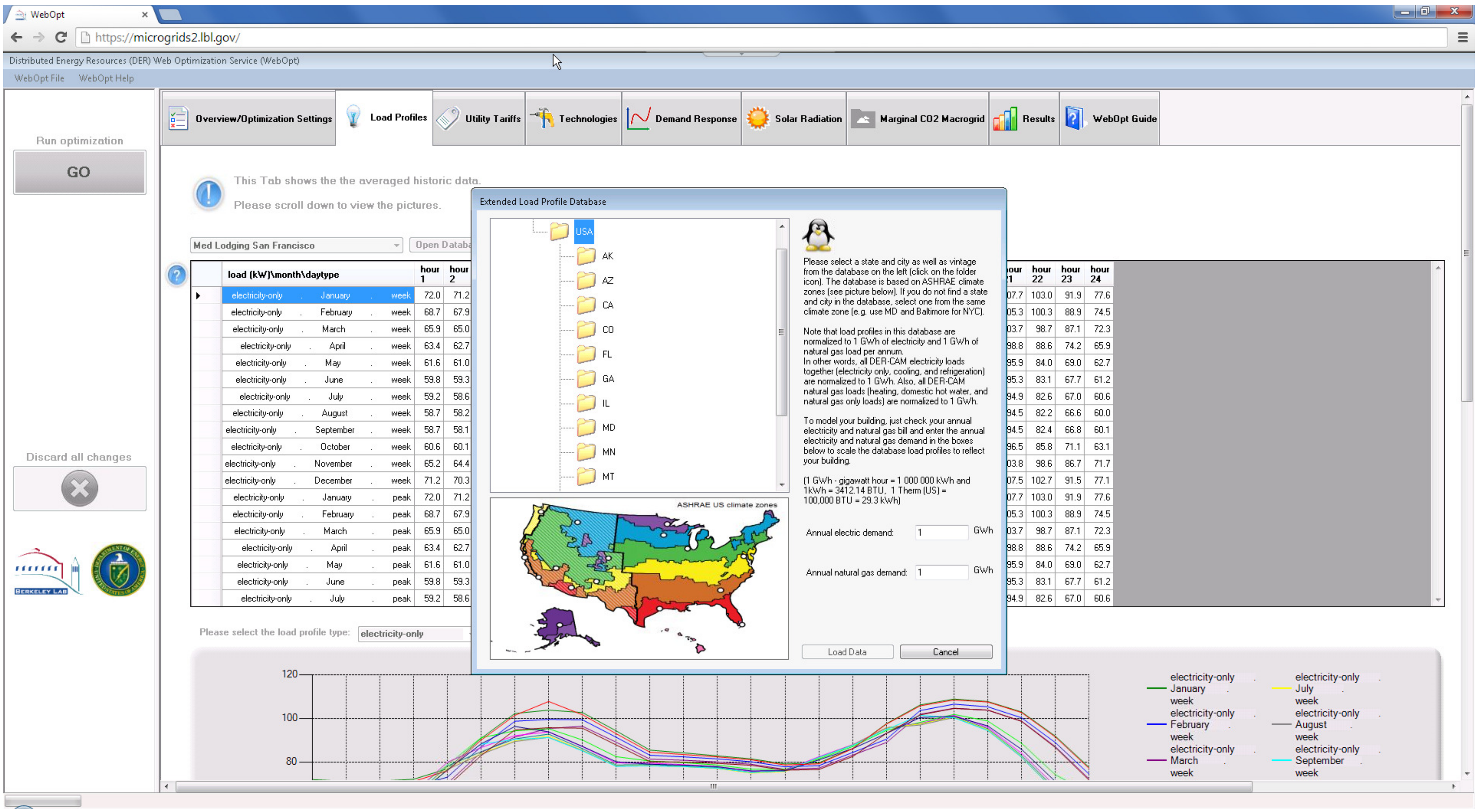


DER-CAM DECISION SUPPORT TOOL FOR DECENTRALIZED ENERGY SYSTEMS

ANALYTICS | PLANNING | OPERATIONS

DER-CAM DECISION SUPPORT TOOL FOR DECENTRALIZED ENERGY SYSTEMS

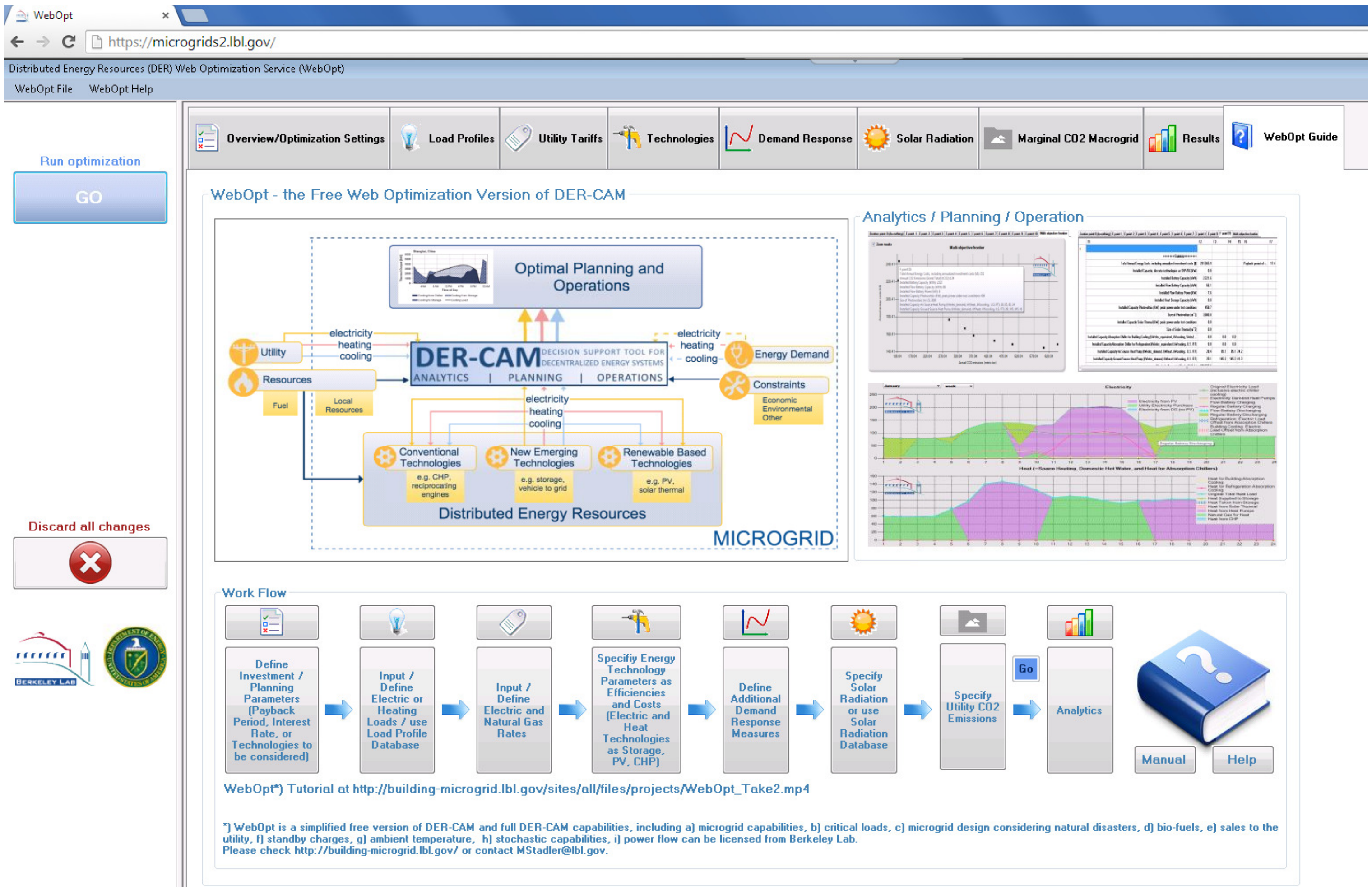
ANALYTICS | PLANNING | OPERATIONS



DER-CAM DECISION SUPPORT TOOL FOR DECENTRALIZED ENERGY SYSTEMS

ANALYTICS | PLANNING | OPERATIONS

Transferability: Online DER-CAM User Guide

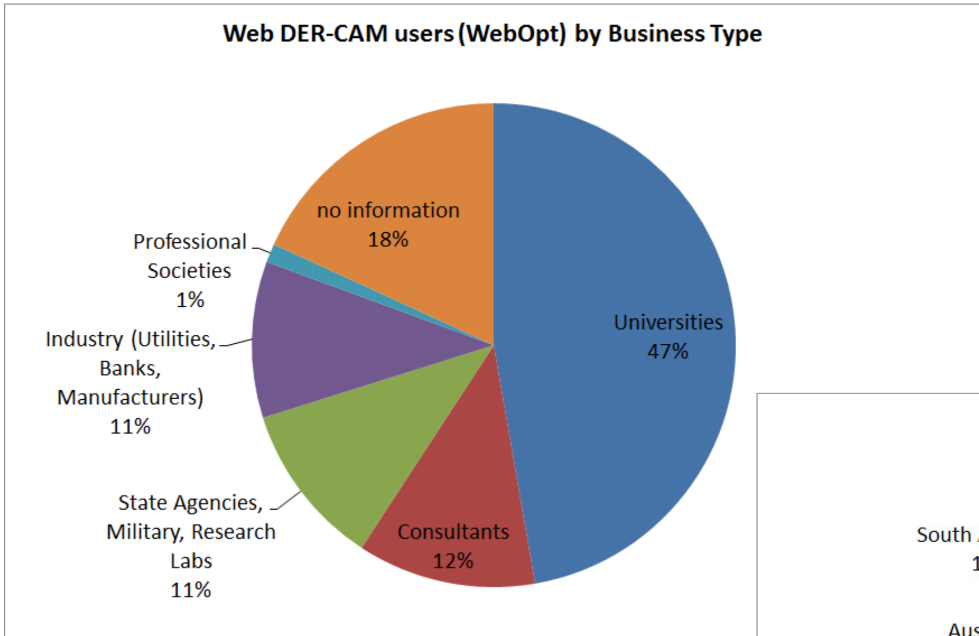


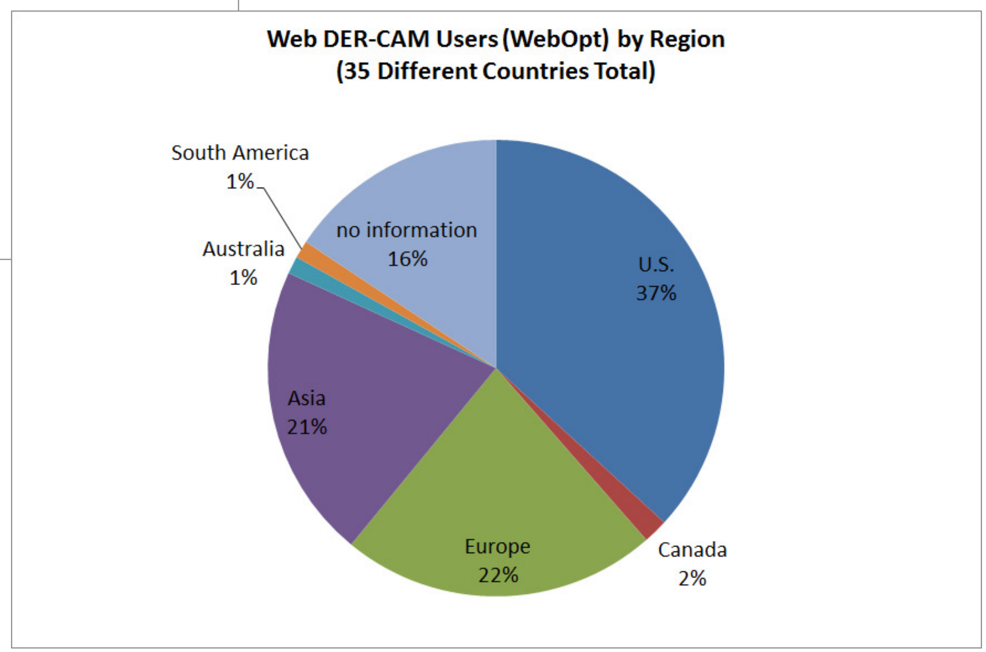
http://building-microgrid.lbl.gov/projects/how-access-der-cam

DER-CAM DECISION SUPPORT TOOL FOR DECENTRALIZED ENERGY SYSTEMS

ANALYTICS | PLANNING | OPERATIONS

WebOpt Statistics





Application

Microgrid Capabilities and Resiliency at Fort Hunter Liggett

DER-CAM DECISION SUPPORT TOOL FOR DECENTRALIZED ENERGY SYSTEMS

ANALYTICS | PLANNING | OPERATIONS

Overview

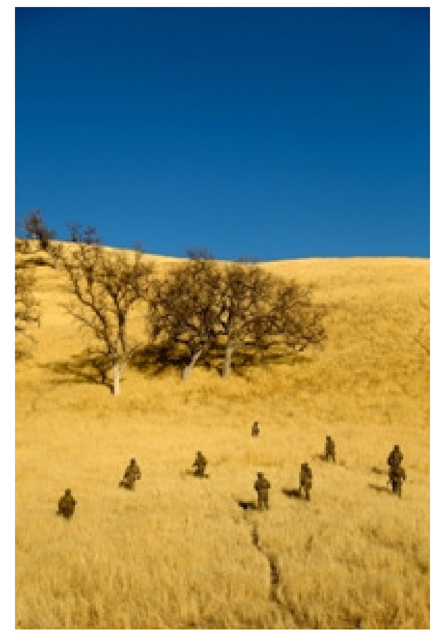
- Training facility for combat support and combat service support units of the Army Reserve
- Largest installation in the Army Reserve (> 165,000 acres)
- Existing DER: 2MW PV + 1MWh battery
- Future: Large (>1MW) PV and battery system to be installed by TriTechnic together with Siemens and the U.S. Army

Objective

Enable Microgrid capabilities and install DER-CAM supervisory controller

DER-CAM Contribution

- Use DER-CAM to gauge optimal capacity of DER
    - Consider additional PV and storage
    - Backup generation
    - Short vs. long duration blackouts
    - Optimal DER capacity



source: http://www.liggett.army.mil/

DER-CAM DECISION SUPPORT TOOL FOR DECENTRALIZED ENERGY SYSTEMS

ANALYTICS | PLANNING | OPERATIONS

Objective: Use DER-CAM to perform a quick assessment on optimal DER at FHL to enable microgrid capabilities. Focus on resilience against natural disasters.

- Blackout cases: none, 3 h, 24 h, 7 days

- Standard DER-CAM assessment (no blackouts):
  - Existing DER
  - Existing DER + additional PV and storage
  - Existing DER + additional DER (full DER-CAM technology range)

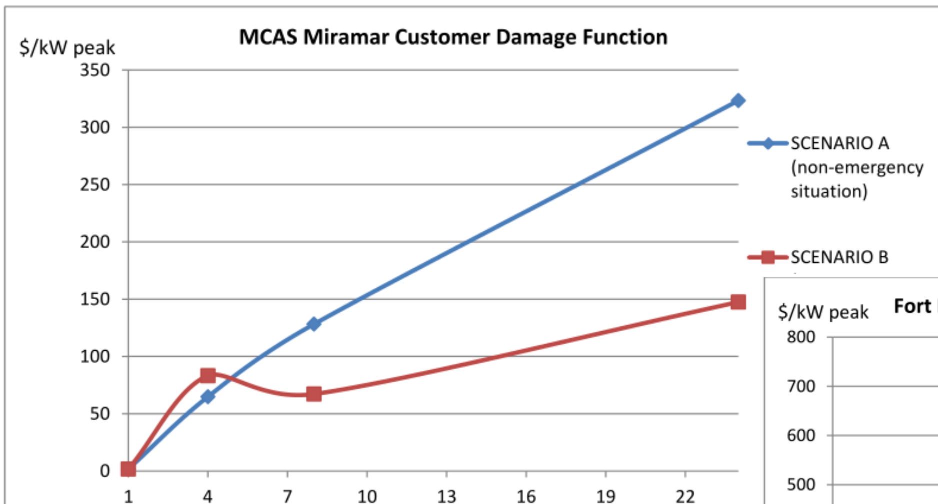
- DER-CAM assessment considering blackouts:
  - Existing DER
  - Existing DER + additional PV and storage
  - Existing DER + Diesel backup generators
  - Existing DER + additional PV, batteries and diesel backup generators
  - Existing DER + additional DER (full DER-CAM technology range)

Load prioritizations: 10% Critical loads; 20% Low Priority; 70% Medium priority

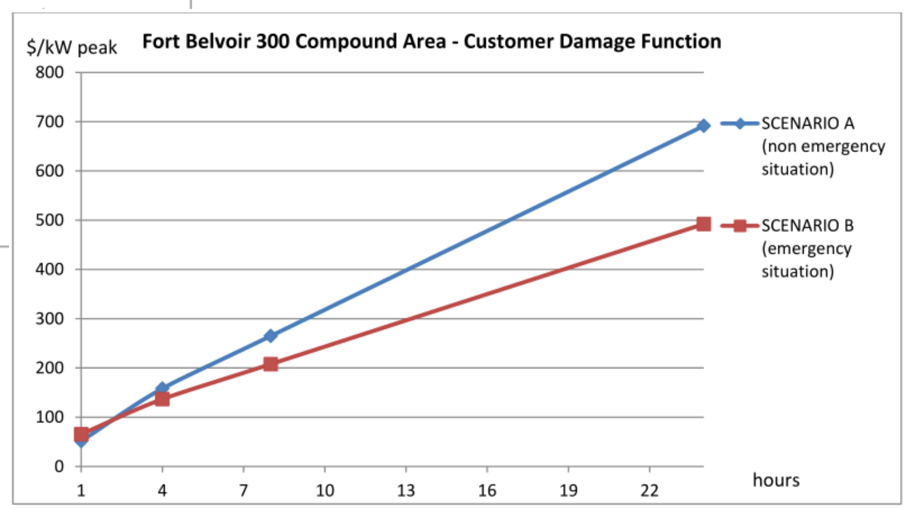
Fort Hunter Liggett – Customer Damage Function (CDF)

Customer Damage Function is used to estimate outage costs as a function of the outage duration.

*Value of Electrical Energy Security (VEES) ~ Outage Duration * $/kW peak * Peak Demand*



Source:
Valuing Energy Security: Customer Damage Function Methodology and Case Studies at DoD Installations, NREL



DER-CAM DECISION SUPPORT TOOL FOR DECENTRALIZED ENERGY SYSTEMS

ANALYTICS | PLANNING | OPERATIONS

Standard DER-CAM assessment - no blackouts

Key Results*)

	BAU/Actual	Additional PV + Storage	All possible DER in DER-CAM
Annual Total Costs, million USD	3.035	2.948	2.701
Annual CO_2 emissions, ton	4967	4161	4454
Photovoltaic, kW	2000	3032	2069
Electric Storage, kWh	1000	4141	1251
ICE, kW	-	-	2000
CHP: ICE + HX, kW	-	-	500
Absorption Chiller, kW	-	-	2828
Solar Thermal, kW	-	-	784

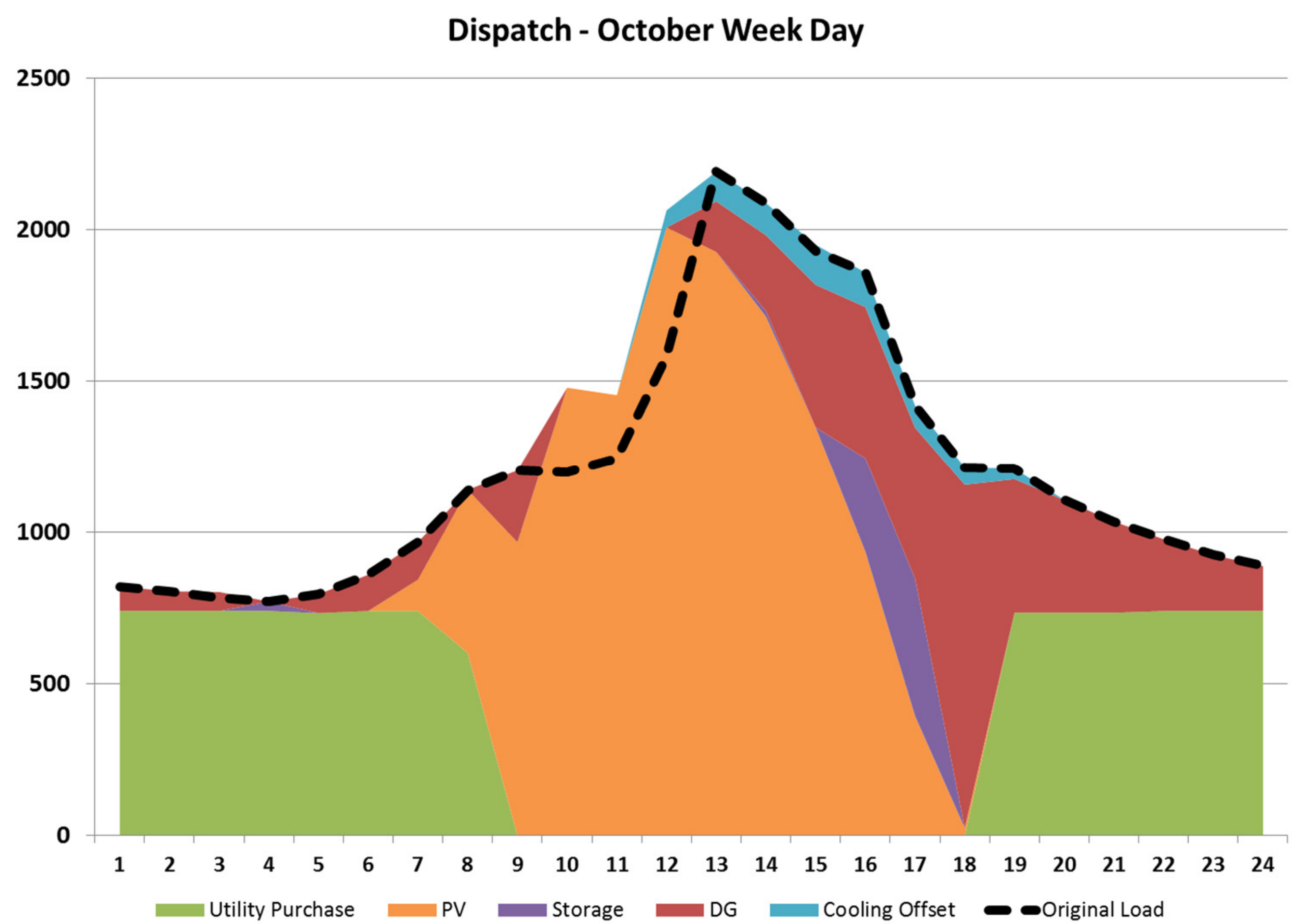
- Allowing additional PV and storage shows that the optimal investment capacity is higher, which is in accordance with the existing expansion plans of FHL
- Allowing other DER shows potential to reduce energy costs by up to 11% and CO_2 reductions by 10%

*) Sales are not part of this analysis

DER-CAM DECISION SUPPORT TOOL FOR DECENTRALIZED ENERGY SYSTEMS

ANALYTICS | PLANNING | OPERATIONS

Standard DER-CAM assessment - no blackouts



All DER technologies allowed

PV generation enables frequent voluntary islanding (no energy purchase during the day)

Fort Hunter Liggett – DER-CAM assessment – with 3h blackout

Key Results*)

(Costs in million USD)	Existing PV and Storage	Existing PV, Storage + Diesel Backup	Additional PV and Storage	Additional PV, Storage and Diesel Backup	All DER
TOTAL COSTS	3.050	3.043	2.948	2.948	2.701
Electricity Costs	2.218	2.218	1.703	1.692	1.147
Fuel Costs	0.320	0.320	0.320	0.320	0.475
Annualized Capital Costs	0.491	0.493	0.915	0.926	0.974
O&M Costs	0.001	0.001	0.001	0.001	0.035
CDF Costs	0.015	0.005	-	-	-
Annual CO_2, ton	4966	4967	4177	4161	4455
Installed capacity					
Photovoltaic, kW	2000	2000	3079	3032	2068
Electric Storage, kWh	1000	1000	3845	4141	1251
Diesel Backup, kW	-	200	-	-	-
ICE, kW	-	-	-	-	2000
ICE HX, kW	-	-	-	-	500
Absorption Chiller, kW	-	-	-	-	2828
Solar Thermal, kW	-	-	-	-	783

- 3h blackout has little to no effect on results
- Existing capacity can be dispatched to meet all electric loads during short duration blackouts (some backup generators already exist at FHL)

*) Sales are not part of this analysis

DER-CAM DECISION SUPPORT TOOL FOR DECENTRALIZED ENERGY SYSTEMS

ANALYTICS | PLANNING | OPERATIONS

Fort Hunter Liggett – DER-CAM assessment - 24h blackout

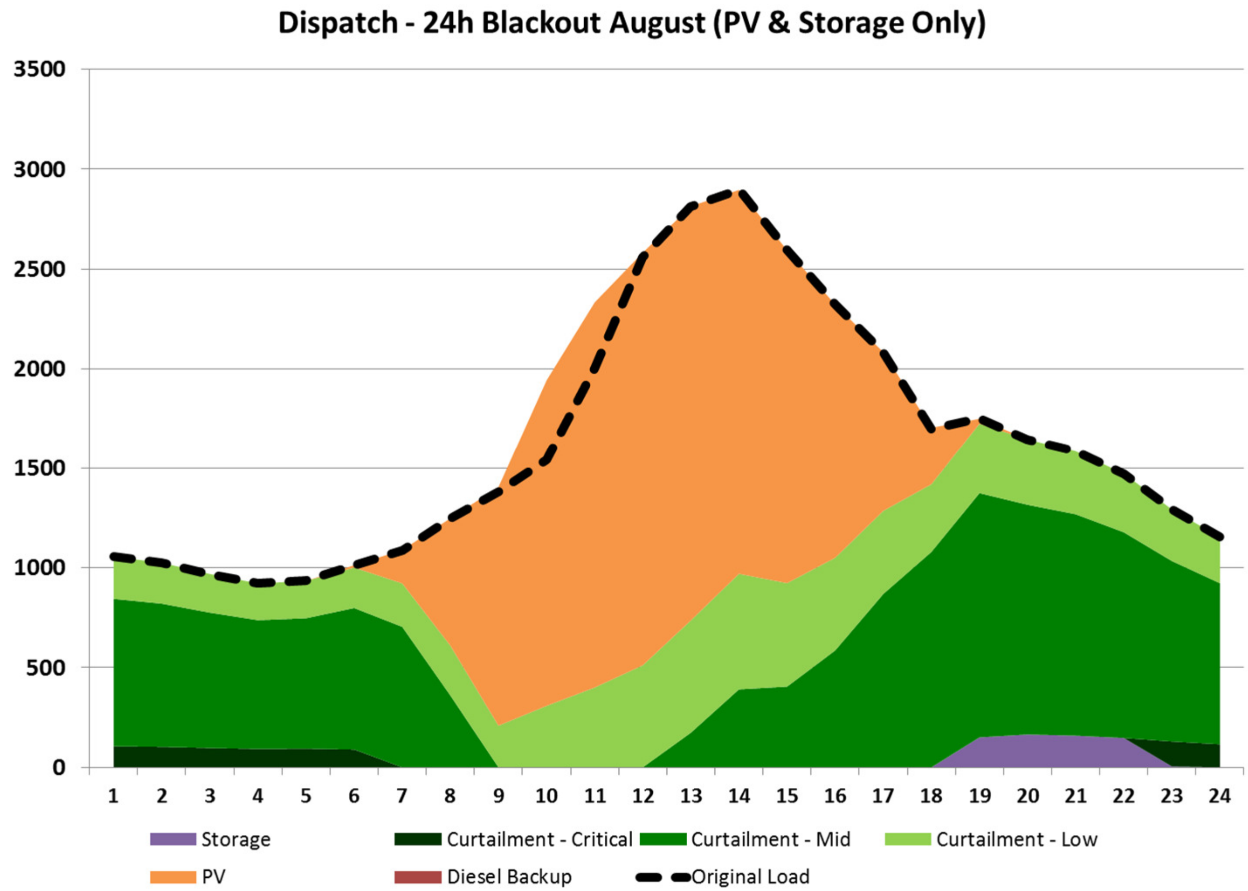
Key Results*)

(Costs in million USD)	Existing PV and Storage	Existing PV, Storage + Diesel Backup	Additional PV and Storage	Additional PV, Storage and Diesel Backup	All DER
TOTAL COSTS	5.363	3.068	3.655	2.976	2.702
Electricity Costs	2.216	2.216	0.785	1.661	1.145
Fuel Costs	0.320	0.326	0.320	0.324	0.477
Annualized Capital Costs	0.491	0.510	2.475	0.971	0.976
O&M Costs	0.001	0.001	0.001	0.001	0.036
CDF Costs	2.330	0.009	0.059	0.010	0.000
Annual CO_2, ton	4955	4973	2132	4119	4444
Installed Capacity					
Photovoltaic, kW	2000	2000	4936	3106	2077
Electric Storage, kWh	1000	1000	20709	4374	1250
Diesel Backup, kW	-	1400	-	1000	-
ICE, kW	-	-	-	-	2000
ICE HX, kW	-	-	-	-	500
Absorption Chiller, kW	-	-	-	-	2807
Solar Thermal, kW	-	-	-	-	801

- Results show that additional PV and storage, in addition to backup generation, will allow FHL to survive 24h outages without any major service disruption at low costs – diesel consumption roughly 1250 gallons for 24h
- When considering all DER options, the optimal investment solution allows enough flexibility to maintain operation during 24h outages and lowest costs

*) Sales are not part of this analysis

24h blackouts, only PV and storage

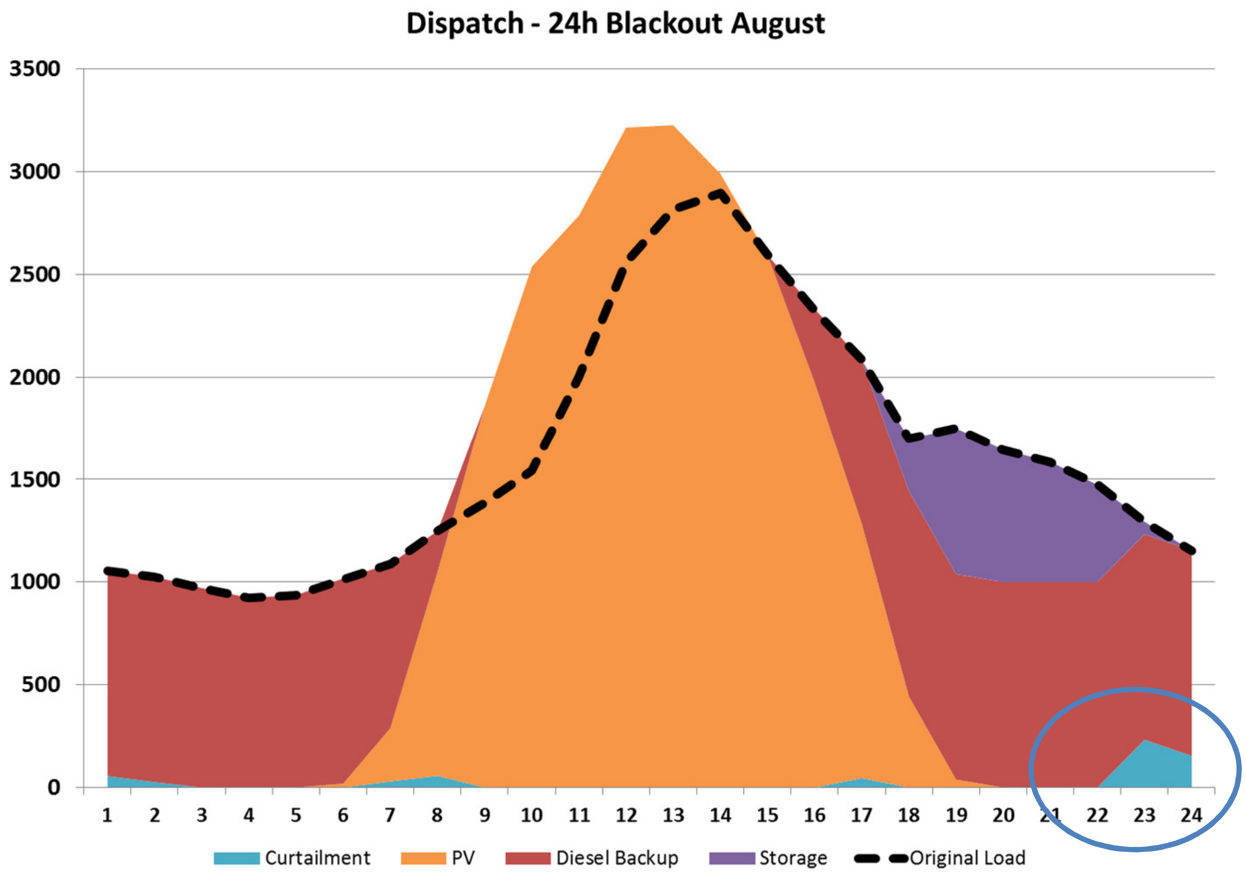


With the current PV and storage capacity alone, FHL would have severe curtailments in the event of a 24h outage, and would not be able to supply all loads

DER-CAM DECISION SUPPORT TOOL FOR DECENTRALIZED ENERGY SYSTEMS

ANALYTICS | PLANNING | OPERATIONS

24h blackouts with PV, storage, and diesel backup generators



Only PV, Batteries, and Backup Generators allowed

some load curtailment

Planned expansion of PV and Storage, together with diesel backup generators will allow increased resilience at FHL

DER-CAM assessment – 7 day blackout

- Extremely high costs in prolonged outages with current resources (with existing equipment 24 millionUSD, all DER allowed only 3 millionUSD)
- Additional backup capacity increases significantly (up to 8 MW)
- Considering the capacity of DER to be implemented at FHL, the ability to maintain operation during prolonged blackout periods relies only on the size of fuel storage (fuel storage sizing) – consumption during blackouts approx. 3300 gallon LNG (12 500 liter)

Application

Cooling at the University of New Mexico

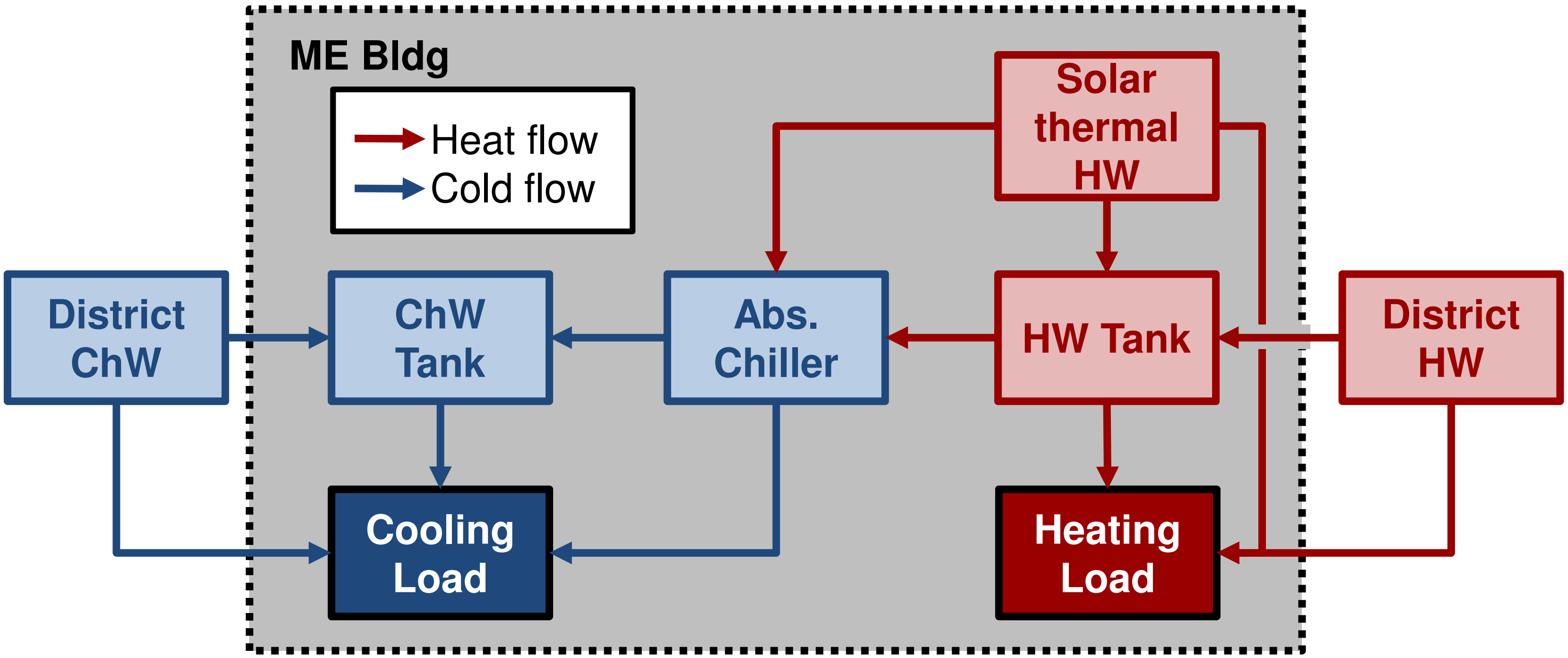
objectives:

- generate optimized scheduling of cooling equipment with Operations DER-CAM
  - solar thermal collection
  - hot water storage
  - chilled water storage
  - absorption chiller

- deliver results daily via automated interface to UNM building control system (delta controller)

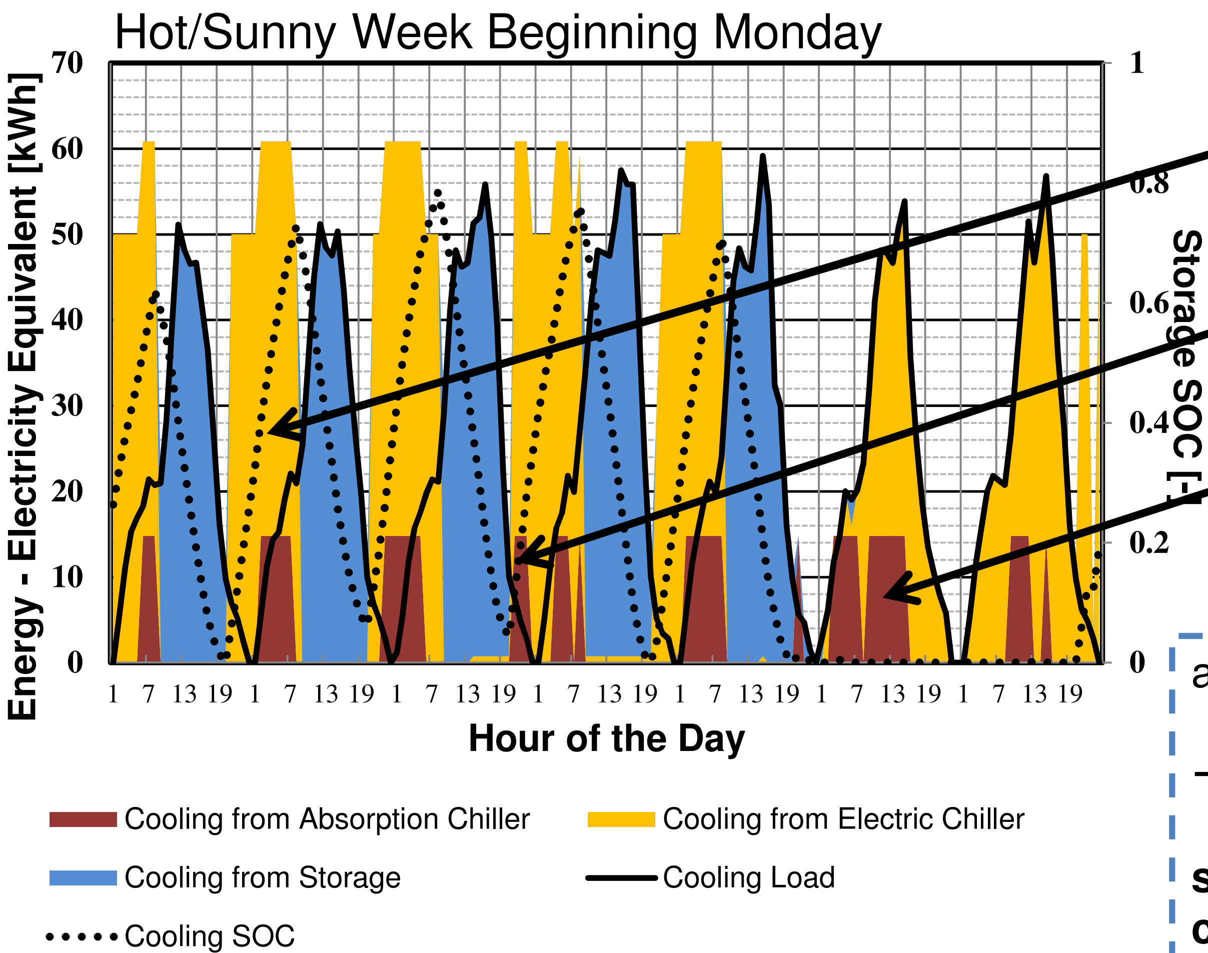
UNM Test Equipment/Configuration

THE UNIVERSITY of NEW MEXICO



<u>equipment capacities:</u>
– solar thermal: 170 kW peak rating
– absorption chiller: 70 kW
– chilled water storage: 3800 kWh
– hot water storage: 300 kWh (9000 gallons)
(all values thermal)

UNM: Cooling Results



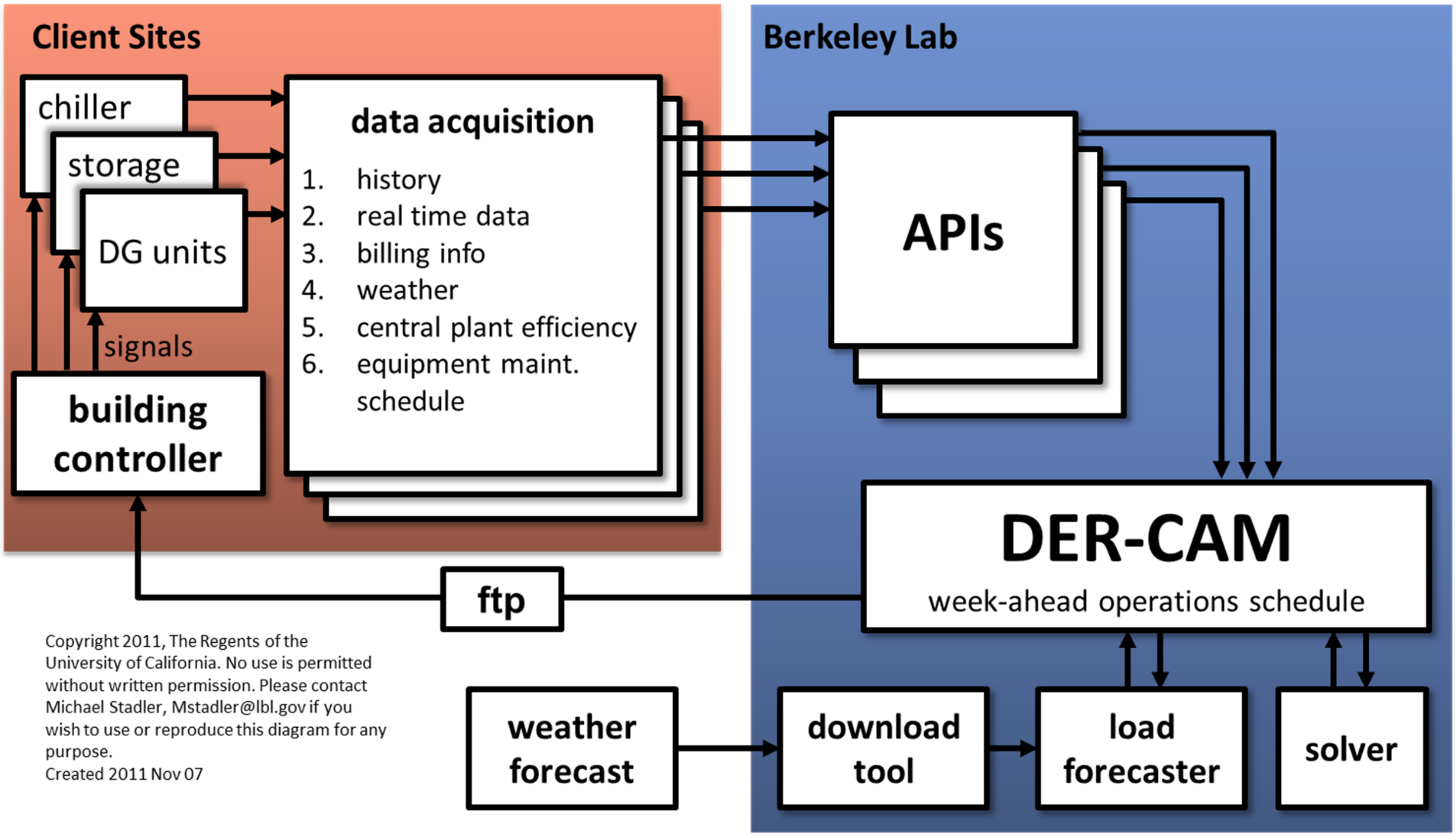
- cold storage recharged during cheap off-peak hours
- abs. chiller runs off-peak to avoid chiller pumping costs
- abs. chiller constrained to 2 cycles per day

automated delivery of results

→

saves up to 29% in energy costs

UNM SaaS Structure



Application

Battery Scheduling at the Santa Rita Jail

DR and Battery at Santa Rita Jail (SRJ)

objectives:

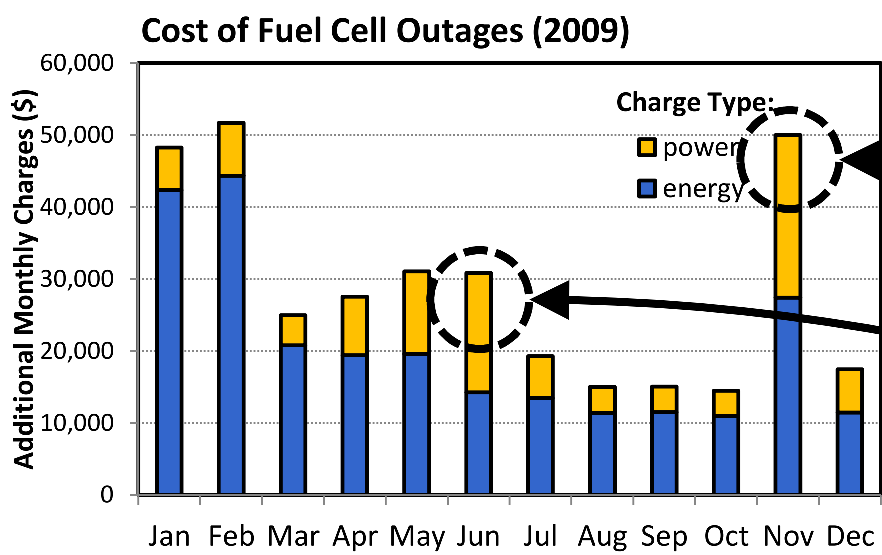
- deliver optimized week-ahead scheduling of onsite electric storage with Operations DER-CAM
- determine potential reduction in utility feeder peak demand through *strategic battery dispatch*

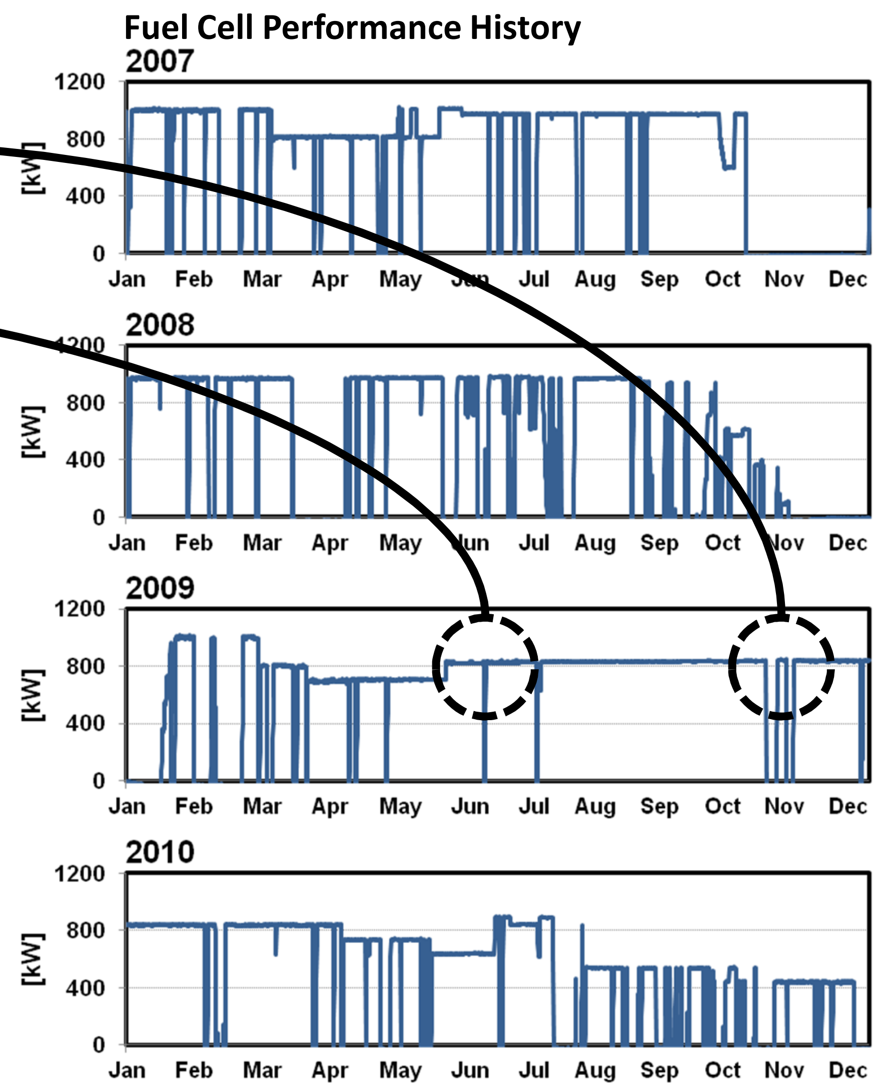
- 3 MW peak load facility
- CERTS microgrid functionality

DER On-site:

- photovoltaic: 1.2 MW peak
- fuel cell: 1 MW molten carbonate
- electric storage: 2 MW 2MWh Li-ion

Problems with Generation





–fuel cell experiences frequent outages

–even short outages can have significant economic impacts, by setting monthly power demand charges

–How can this be avoided?

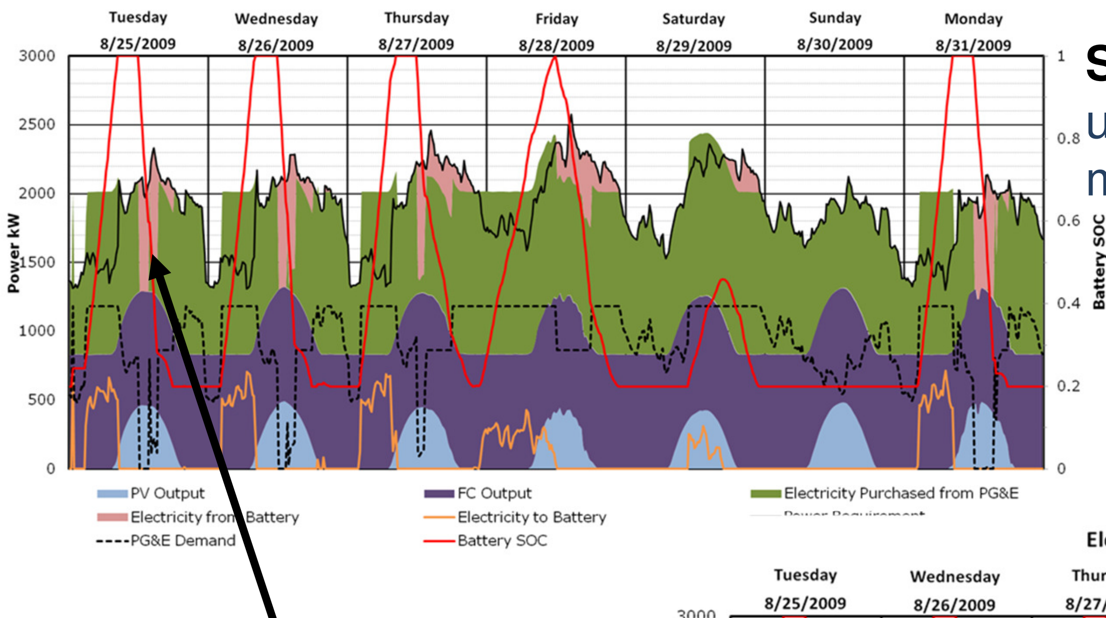
DR with Electric Storage

DER-CAM DECISION SUPPORT TOOL FOR DECENTRALIZED ENERGY SYSTEMS

ANALYTICS | PLANNING | OPERATIONS

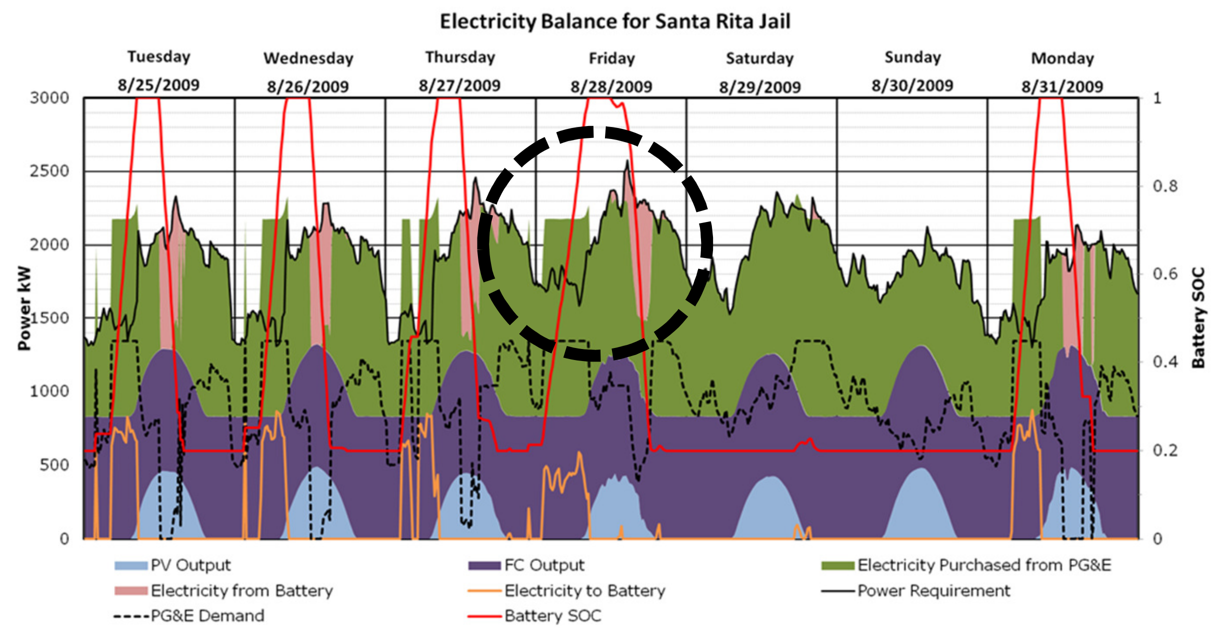
SRJ: Optimal Schedules*

Solution 1: utility bill minimization



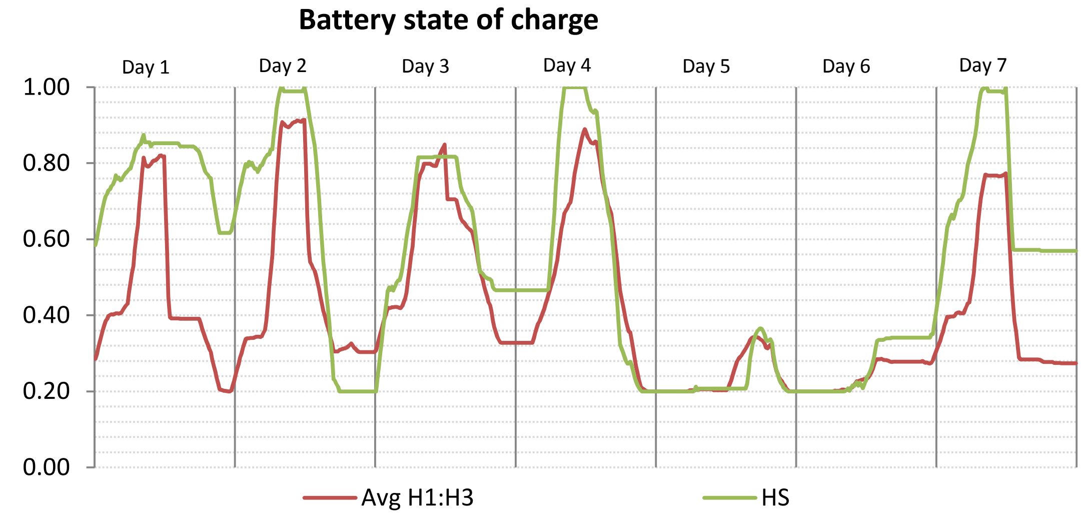
DER-CAM minimizes on-peak purchases due to high demand charge

Solution 2: feeder peak minimization +$3.8k demand charge 3.5% reduction



***Jail-Only Results**
(note scale)

SRJ: Optimal Schedules with Uncertainty



Avg. H1:H3 – Average of optimal battery schedules H1 to H3, obtained from fuel cell availability scenarios 1 to 3.

HS – Optimal battery schedule obtained by the stochastic model, where all scenarios are considered simultaneously.

Observed fuel cell scenario	1		2		3	
Battery schedule	Avg. H1:H3	HS	Avg. H1:H3	HS	Avg. H1:H3	HS
Total energy costs	$ 70 296	$ 69 126	$ 59 017	$ 57 560	$ 64 213	$ 60 431
TOU charges	$ 26 807	$ 26 837	$ 21 245	$ 21 351	$ 23 232	$ 21 821
Demand charges	$ 42 705	$ 41 567	$ 29 596	$ 28 160	$ 35 661	$ 30 968

- optimal battery schedules can be obtained assuming availability scenarios separately (deterministic approach) or simultaneously (stochastic approach)
- the stochastic approach results in a more conservative schedule as well as lower energy costs when unexpected events occur

End

Thank you!

Questions and comments are very welcome.

Feature

Passive Measures

Trade off between Costs and CO_2

Investment DER-CAM: multi-objective frontier (minimize the combination of costs and CO_2 emissions for building)

$$\min\{ (1-\omega) * \frac{Cost}{RefCost} + \omega * \frac{CO_2Em}{RefCO_2Em} \}$$

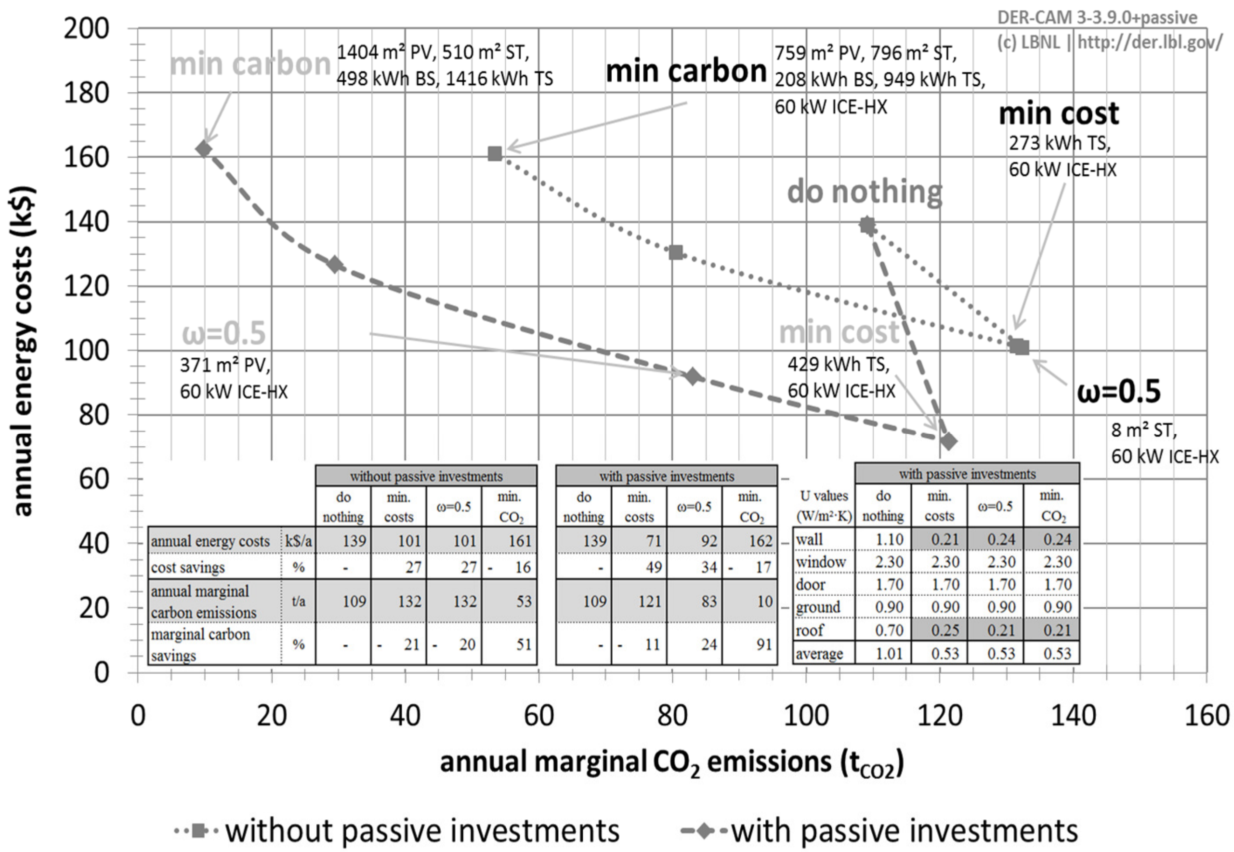
Cost	*total building energy costs including amortized capital costs*
CO_2Em	*total building CO_2 emissions*
ω	*weight factor (0..1)*
$RefCO_2Em$	*parameter to make equation unit less*
RefCost	*parameter to make equation unit less.*

Passive Measures have Costs but Change the Loads Directly

$$\min C = \sum_{m} \mathrm{MFix}_{m} + \sum_{m,d,h} u_{u,m,d,h} \cdot \mathrm{C}_{u,m,d,h} + \sum_{u,p} \max u_{u,p} \cdot \mathrm{D}_{u,p} + \sum_{g} num_{g} \cdot \mathrm{IFix}_{g} \cdot \mathrm{ANN}_{g}$$
$$+ \sum_{(c,s)} \left(pur_{(c,s)} \cdot \mathrm{IFix}_{(c,s)} + cap_{(c,s)} \cdot \mathrm{IVar}_{(c,s)} \right) \cdot \mathrm{ANN}_{(c,s)}$$
$$+ \sum_{i,u,m,d,h} \frac{gen_{i,u,m,d,h}}{\eta_{i}} \cdot \mathrm{GENC}_{i,u,m,d,h} + \sum_{u,m,d,h} dr_{u,m,d,h} \cdot \mathrm{DRC}_{u,m,d,h}$$
$$- \sum_{j,u,m,d,h} sell_{j,u,m,d,h} \cdot \mathrm{S}_{m,d,h} + \sum_{b,k} \left(inv_{b,k} \cdot \mathrm{A}_{b} \cdot \left(\mathrm{MAT}_{b,k} + \mathrm{INST}_{b,k} \right) \cdot \mathrm{ANN}_{b,k} \right)$$

$$\mathrm{LOAD}'_{u,m,d,h} = \mathrm{LOAD}_{u,m,d,h} - \sum_{b,k} \left(inv_{b,k} \cdot \left(\mathrm{U}'_{b,k} - \mathrm{U}_{b} \right) \cdot \mathrm{A}_{b} \cdot \mathrm{Fx}_{b} \right) \cdot \Delta \mathrm{T}_{u,m,d,h} \quad : u \in \{cl, sh\}$$

Passive Measures and DER at Campus Building



		without passive investments				with passive investments			
		do nothing	min. costs	ω=0.5	min. CO_2	do nothing	min. costs	ω=0.5	min. CO_2
annual energy costs	k$/a	139	101	101	161	139	71	92	162
cost savings	%	-	27	27	- 16	-	49	34	- 17
annual marginal carbon emissions	t/a	109	132	132	53	109	121	83	10
marginal carbon savings	%	-	- 21	- 20	51	-	- 11	24	91

U values ($W/m^2 \cdot K$)	with passive investments: do nothing	min. costs	ω=0.5	min. CO_2
wall	1.10	0.21	0.24	0.24
window	2.30	2.30	2.30	2.30
door	1.70	1.70	1.70	1.70
ground	0.90	0.90	0.90	0.90
roof	0.70	0.25	0.21	0.21
average	1.01	0.53	0.53	0.53

can enable zero carbon microgrid

Feature

Critical Loads

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

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

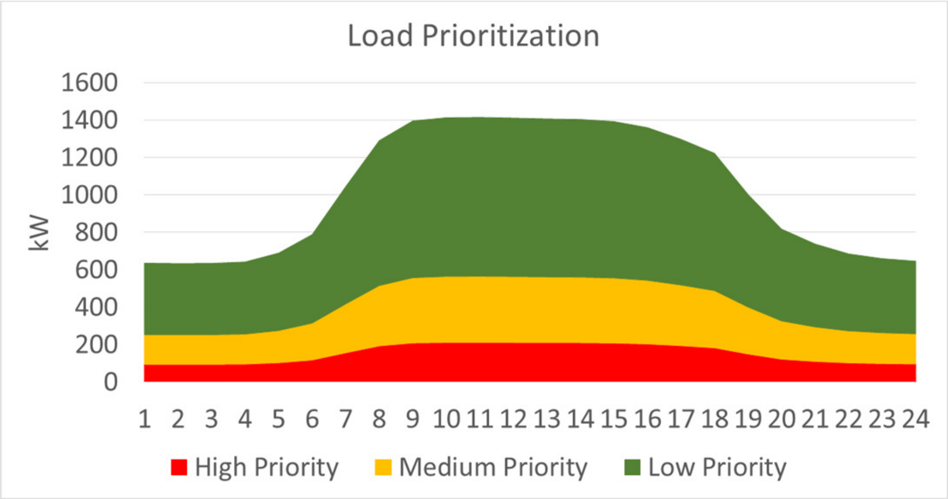
Fix_m	fixed costs in month m
Inv_i	investment decision on technology I, *continuous* versus *discrete* technologies
$InvCost_i$	annualized investment cost of technology i
p_ω	probability of scenario ω
$OpCost_{\omega,m,t,h}$	microgrid operation costs in scenario, month m, day type t, hour h

Critical Loads

- whenever load prioritization is necessary, we may define critical loads / load priorities in DER-CAM

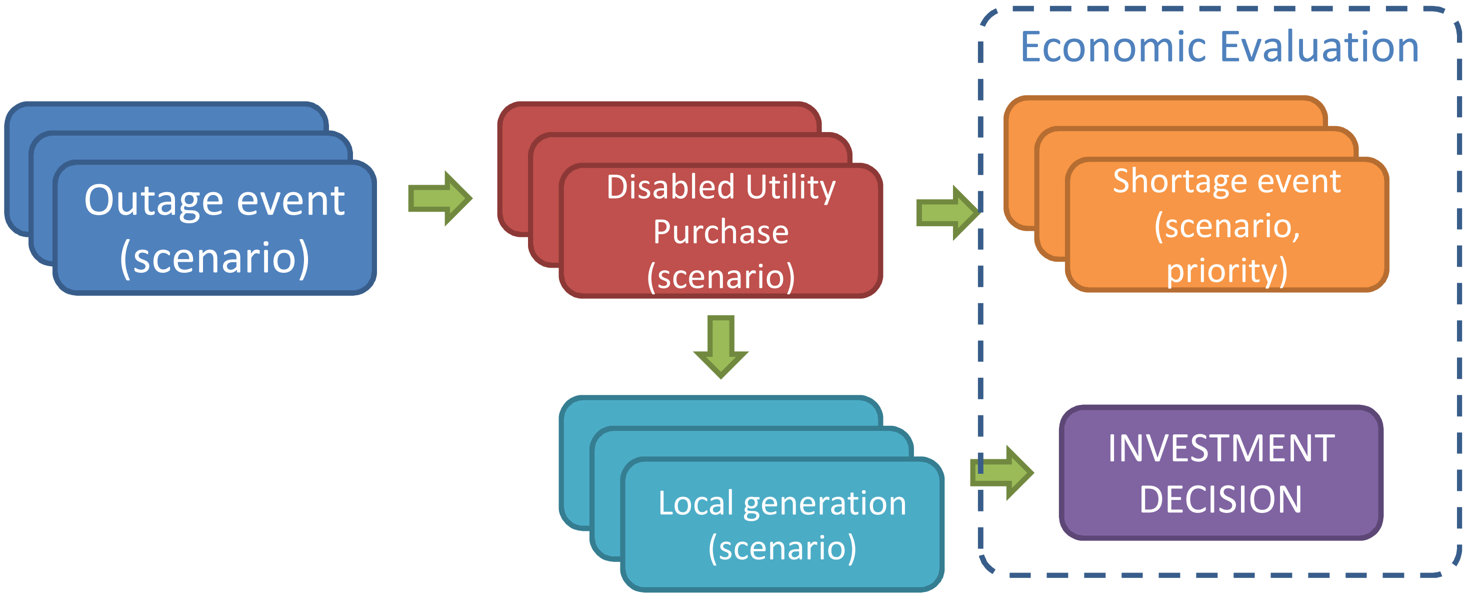
- critical load / load prioritization may occur both during outages and demand response interventions

- load priorities may be set to three different levels for both outages and demand response events: *low, mid, high*



Outages

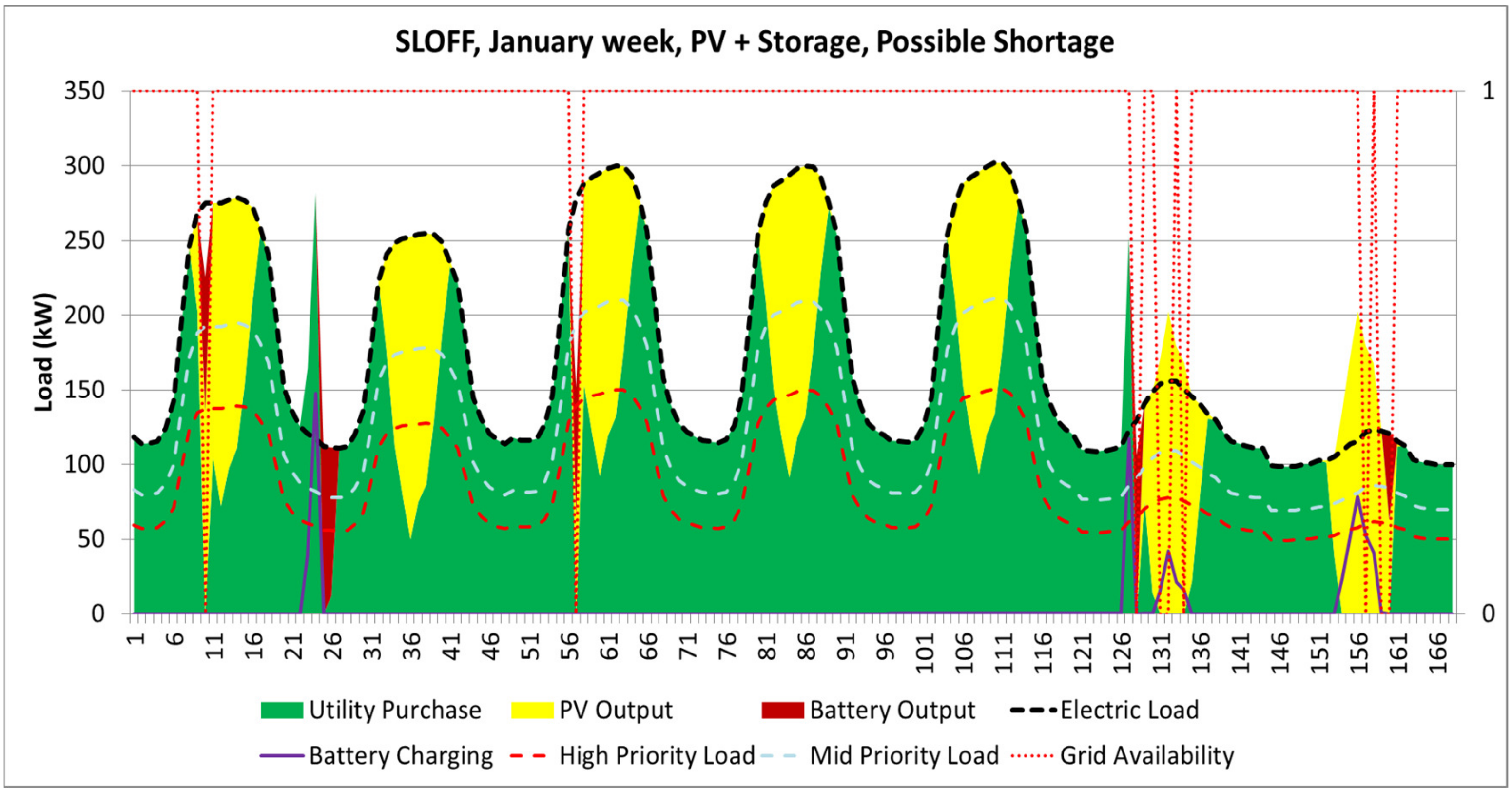
- utility grid outage events can trigger shortages, which can be set to different load priorities, although loads can also be met by local generation
- this approach has been implemented in the s*tochastic version of DER-CAM*, allowing multiple grid outage scenarios to be considered simultaneously, which has a direct influence on DER Investment decisions



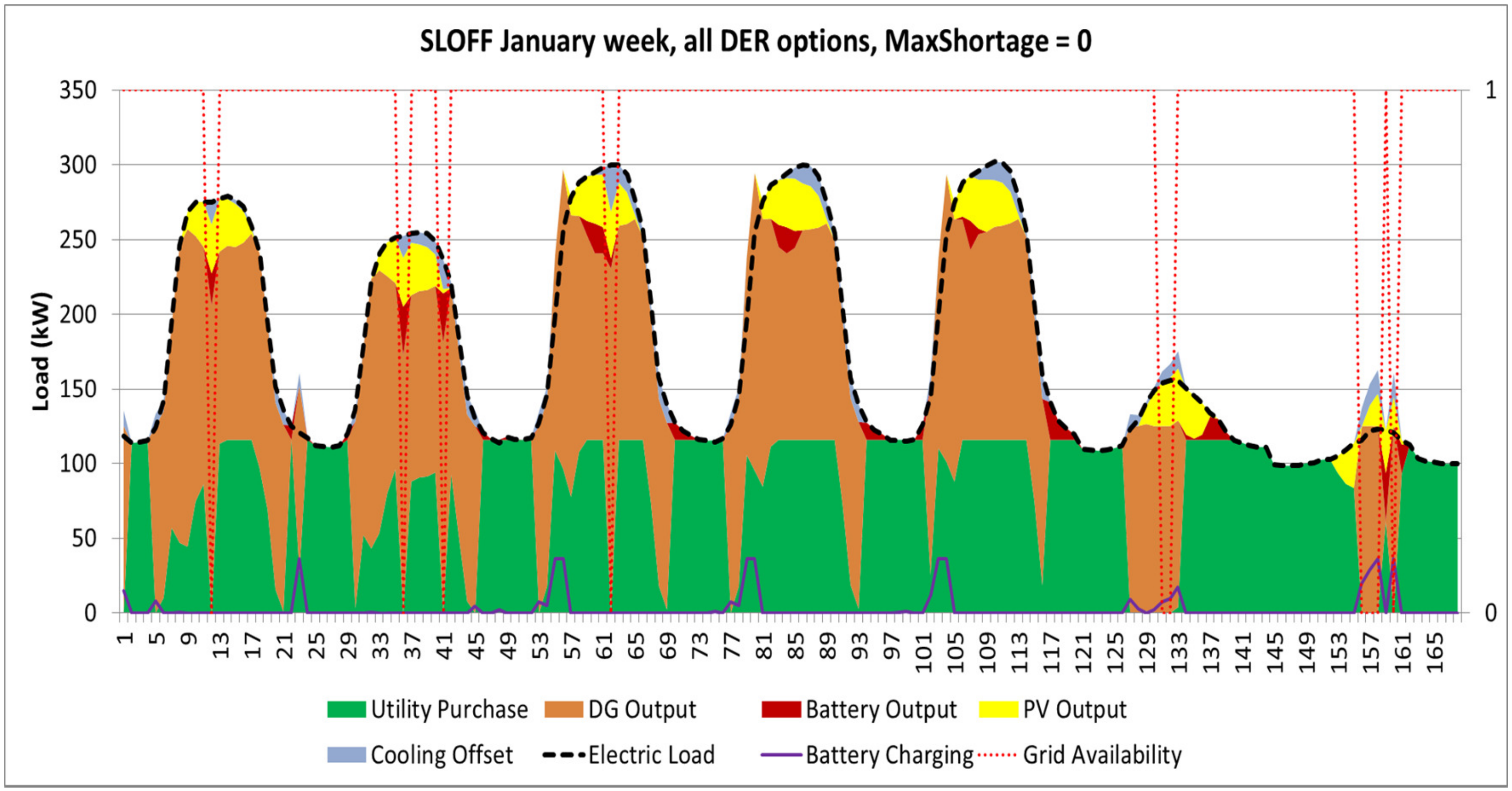
DER-CAM DECISION SUPPORT TOOL FOR DECENTRALIZED ENERGY SYSTEMS

ANALYTICS | PLANNING | OPERATIONS

Small Office –
with Allowance of Disruption for low and mid



Small Office – NO Allowance of Disruption for low and mid



Feature

Stepwise Approximation of Non-Linear Efficiency Curves

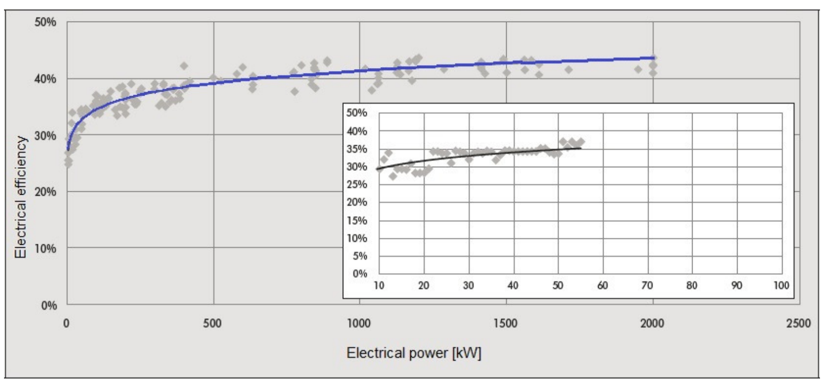
Non-Linear Efficiency Curves – New Modelling of CHP/DG

constant efficiencies problematic since

a) installed capacity affects maximal efficiency

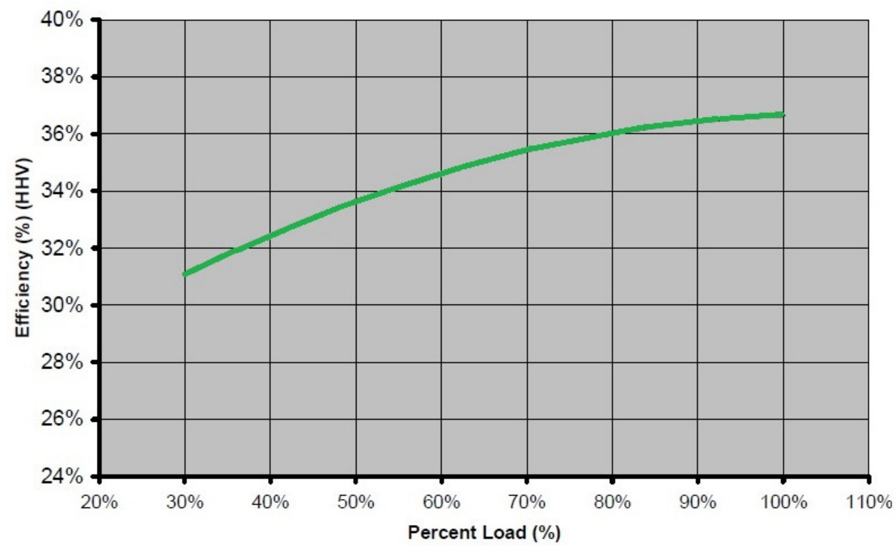
b) part load performance affects actual efficiency

Electrical efficiencies for natural gas powered CHPs based on installed capacities P_{inst}



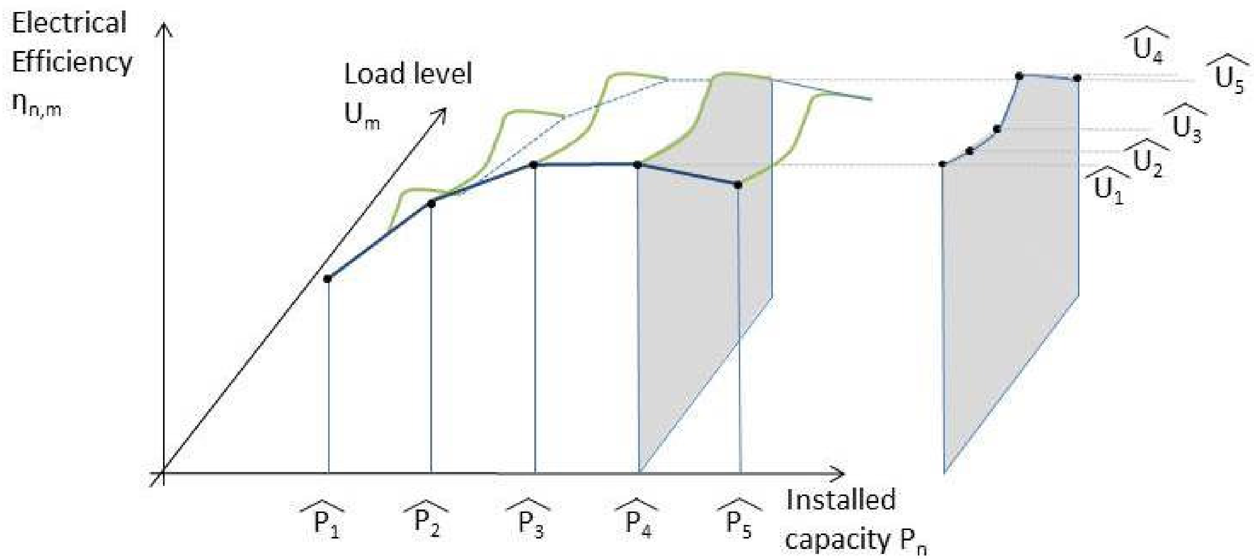
Source: ASUE, 2011

Typical efficiencies for natural gas powered CHPs based on load levels U



Source: EEA, 2008

Stepwise Linear Optimization, SOS



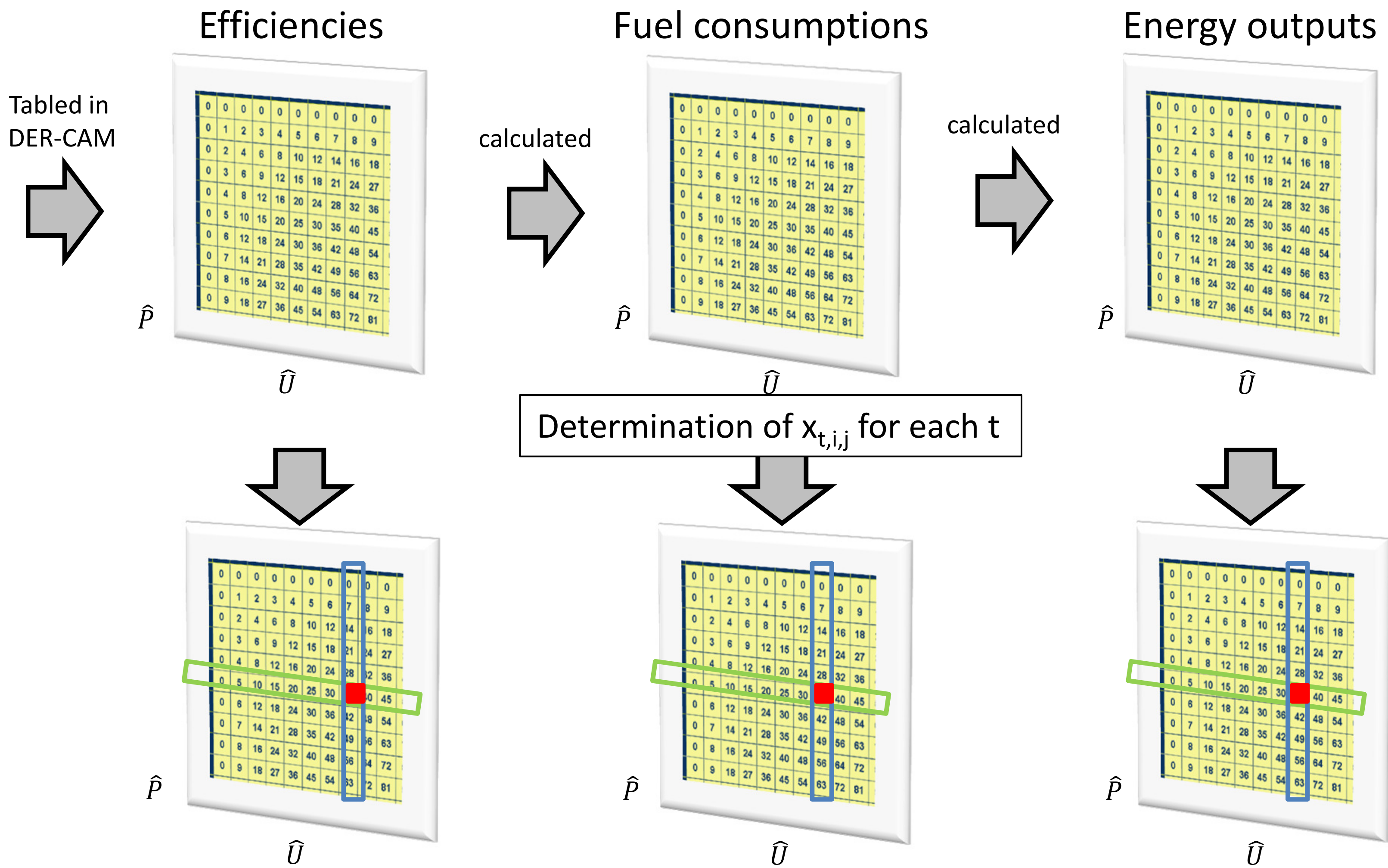
$$\eta_t = f_t(P_{inst}, U_t) = \sum_{i=1}^{n}\sum_{j=1}^{m}\left(f\left(\widehat{P_i}, \widehat{U_{i,j}}\right) * x_{t,i,j}\right)$$

- ⇨ consecutive variables
- ⇨ not more than two adjacent ≠ 0
- ⇨ binary variables avoided, x is a weight factor

$$\sum_{i=1}^{n}\sum_{j=1}^{m} x_{t,i,j} = 1$$

$$x_{t,i,j} \geq 0$$

Implementation in DER-CAM



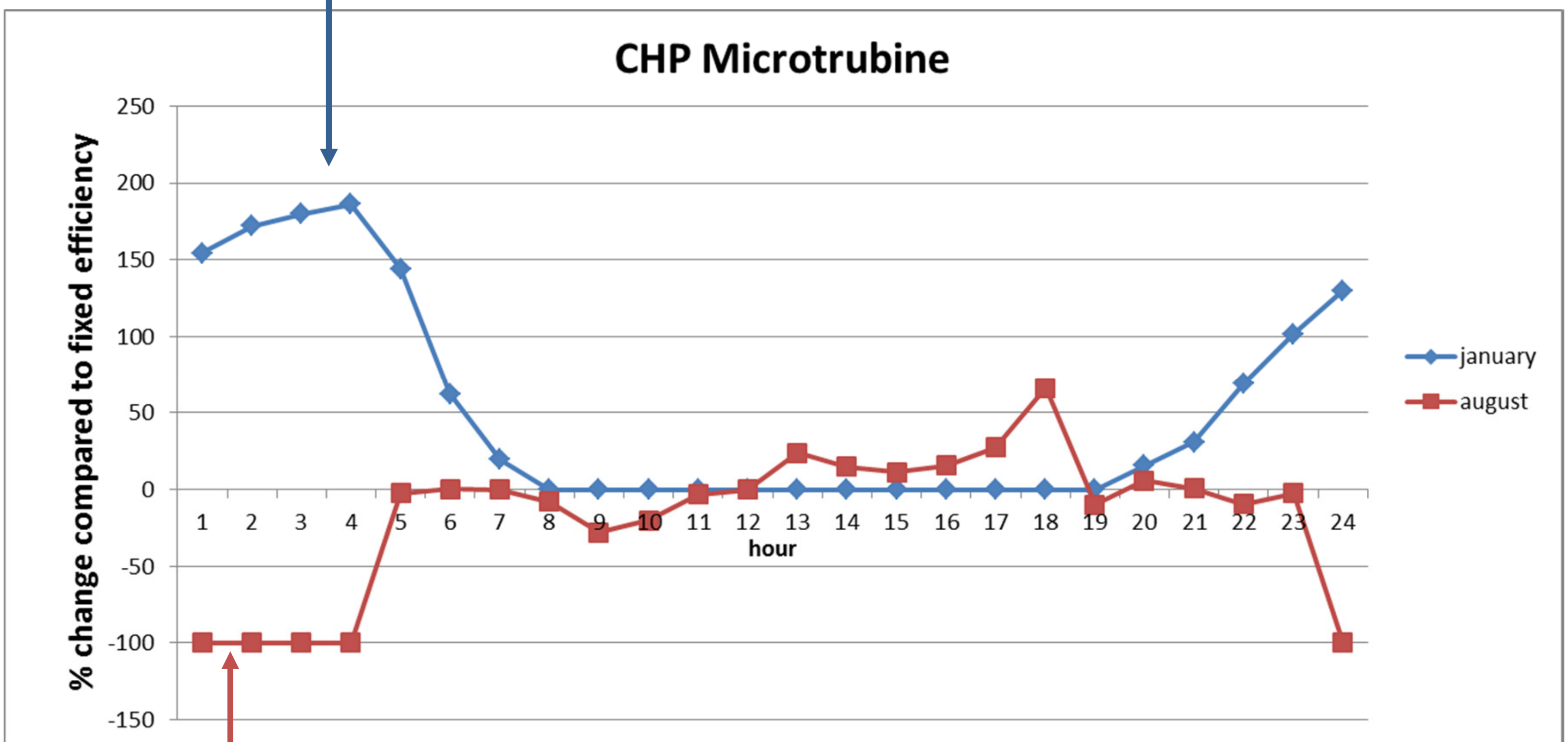
Hospital building in San Francisco
changes of SOS version compared to fixed efficiency, CO_2 minimization

changes compared to the fixed efficiency version	
total costs [%]	1
total CO_2 Emissions [%]	-3
CHP installation [%]	0
PV installation [%]	-100
solar thermal installation [%]	205
heat storage installation [%]	#inf!
elec. generated [%]	1
Elec. purchase [%]	6
NG not used in CHP [%]	-59
NG used in CHP[%]	6

better modelling of CHP efficiency curves impacts mostly PV, solar thermal, and heat storage in this example

Changes in Operational Levels

limited heat storage and solar thermal in winter



due to heat storage and solar thermal in summer

Feature

Temperature Tracking in Heat Storage

Temperature Tracking in Heat Storage

In previous DER-CAM versions:

- thermal energy storage (TES) could only be charged by high temperature (HT) heat sources, i.e. low temperature (LT) heat sources, such as heat pumps, could not be used with the TES

- self-discharging losses were only calculated based on the energy stored in the storage, no difference between the ambient temperature and the water temperature in the tank was considered

Temperature Tracking in Heat Storage

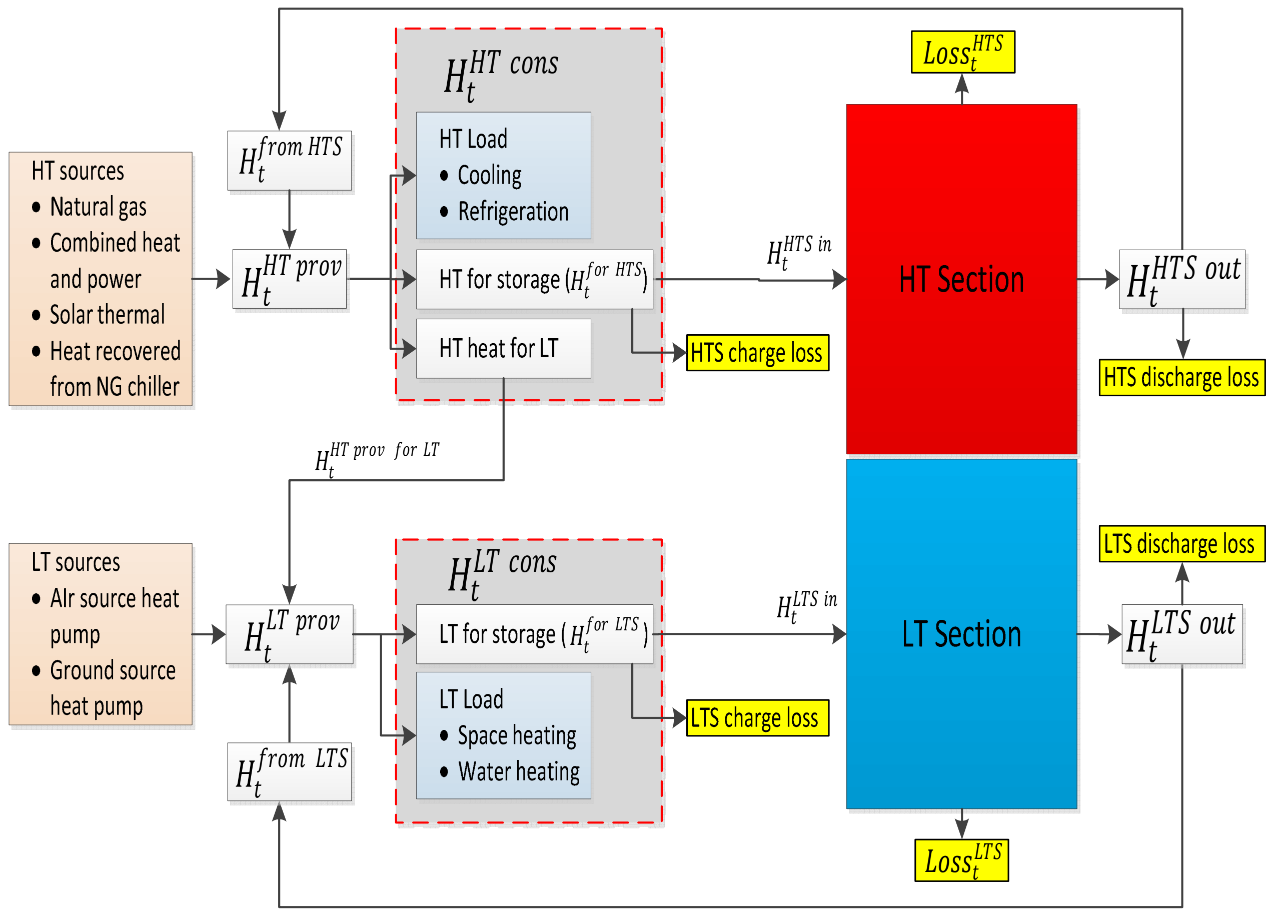
current approach:

- the use of low temperature heat sources is enabled, e.g. heat pumps
- TES is modeled as a storage with two sections (high and low temperature)
- DER-CAM decides both on the total storage size and on the high and low temperature sections
- self-discharging losses are estimated based on the energy stored in the TES and on the difference between the ambient temperature and the water temperature in the TES

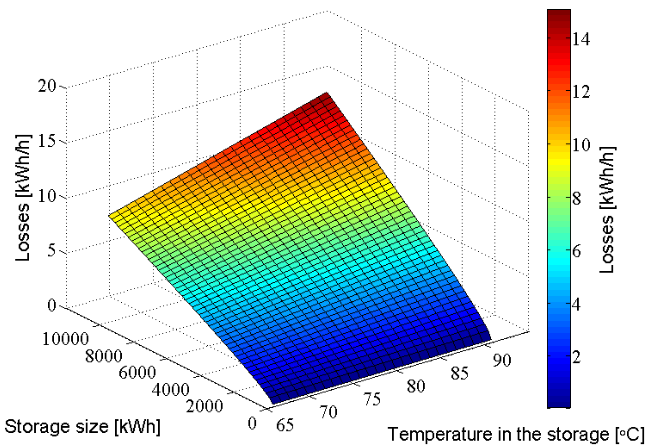
DER-CAM DECISION SUPPORT TOOL FOR DECENTRALIZED ENERGY SYSTEMS

ANALYTICS | PLANNING | OPERATIONS

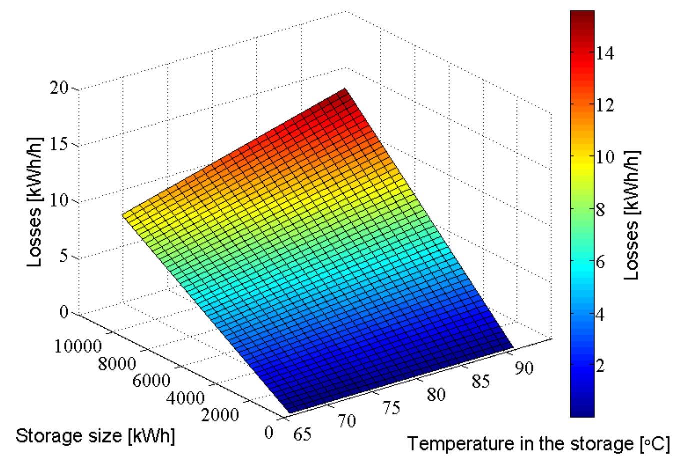
Schematic of New Model



Loss Comparison

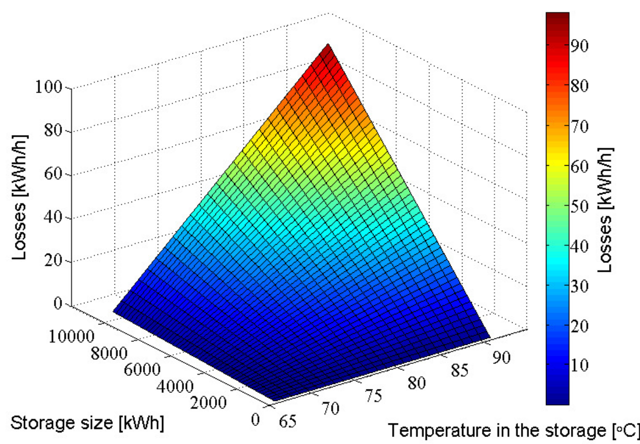


losses for a fully mixed TES



estimated losses for the new TES

losses for old TES



DER-CAM DECISION SUPPORT TOOL FOR DECENTRALIZED ENERGY SYSTEMS

ANALYTICS | PLANNING | OPERATIONS

CA Example Results for CO_2 Minimization

change in optimal technology investment compared to previous DER-CAM

Change in technology investment excl. HP [%]	San Francisco LCOLL	San Francisco LHLTH	San Francisco LHOT	San Diego LCOLL	San Diego LHLTH	San Diego LHOT
DG without HX	**-**	**-**	**-**	**-100**	**inf**	**-**
CHP (DG with HX)	**-7**	**0**	**0**	**24**	**-15**	**0**
Electric Storage	-65	-14	-3	-24	-18	-3
TES (LT section)	-100	-100	-14	158	-5	-28
TES (HT section)	-100	-100	-100	-100	-100	-100
TES (LT + HT section)	**-100**	**-100**	**-14**	**158**	**-5**	**-28**
Abs. Chiller	15	-100	56	21	-20	-5
PV	-7	Inf	-2	0	0	-2
Solar Thermal	-100	-75	21	-	-	14
Annual CO_2 Emissions	7	4	-1	-1	3	0
Annual Energy Costs	-6	0	-1	6	-8	3

Note: '-' means no investment in any model, 'inf' means no investment in old model, '-100' means no investment in new model.

objective function changes marginally, but adopted technologies can change a lot

Feature

Wind Power

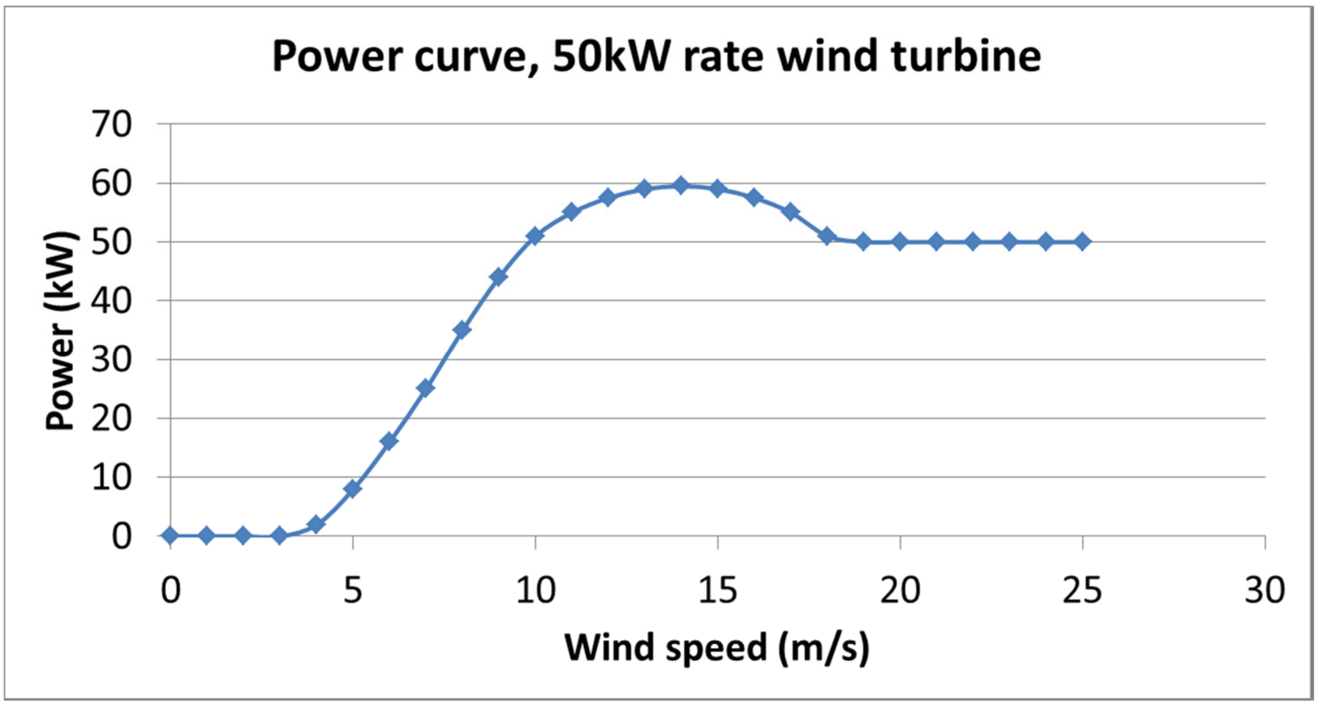
DER-CAM DECISION SUPPORT TOOL FOR DECENTRALIZED ENERGY SYSTEMS

ANALYTICS | PLANNING | OPERATIONS

- DER-CAM now supports wind power in the Deterministic Investment & Planning version
- user is required to input wind speeds, power curve and cost coefficients
- the current time structure used in this DER-CAM version (36 typical days of hourly loads) requires pre-processing of wind data (*vs. 365 daily loads*)
- the spreadsheet pre-processing provides potential wind generation values, which are fed into DER-CAM
- DER-CAM finds the optimal number of wind turbines to be installed at study site.

Time Consistency

- DER-CAM considers 3 (or 7) representative days per month, each described by 24h time steps
- non-linear power curves and cut-in / cut-out speeds lead to high impact of time discretization



Time Consistency

Time	**Wind** m/s	**Power** kW
00:10	2.14	0.00
00:20	2.53	0.00
00:30	3.06	0.13
00:40	3.59	1.18
00:50	3.99	1.97
01:00	4.17	3.04
AVG		
	3.25	1.05

example

In this case, with data sampled from on-site measurements, the average wind speed is below the 3.5 m/s cut-in speed, and yet the energy output is not zero

Time Consistency

- data format required by DER-CAM requires wind output to be processed after wind-power calculations

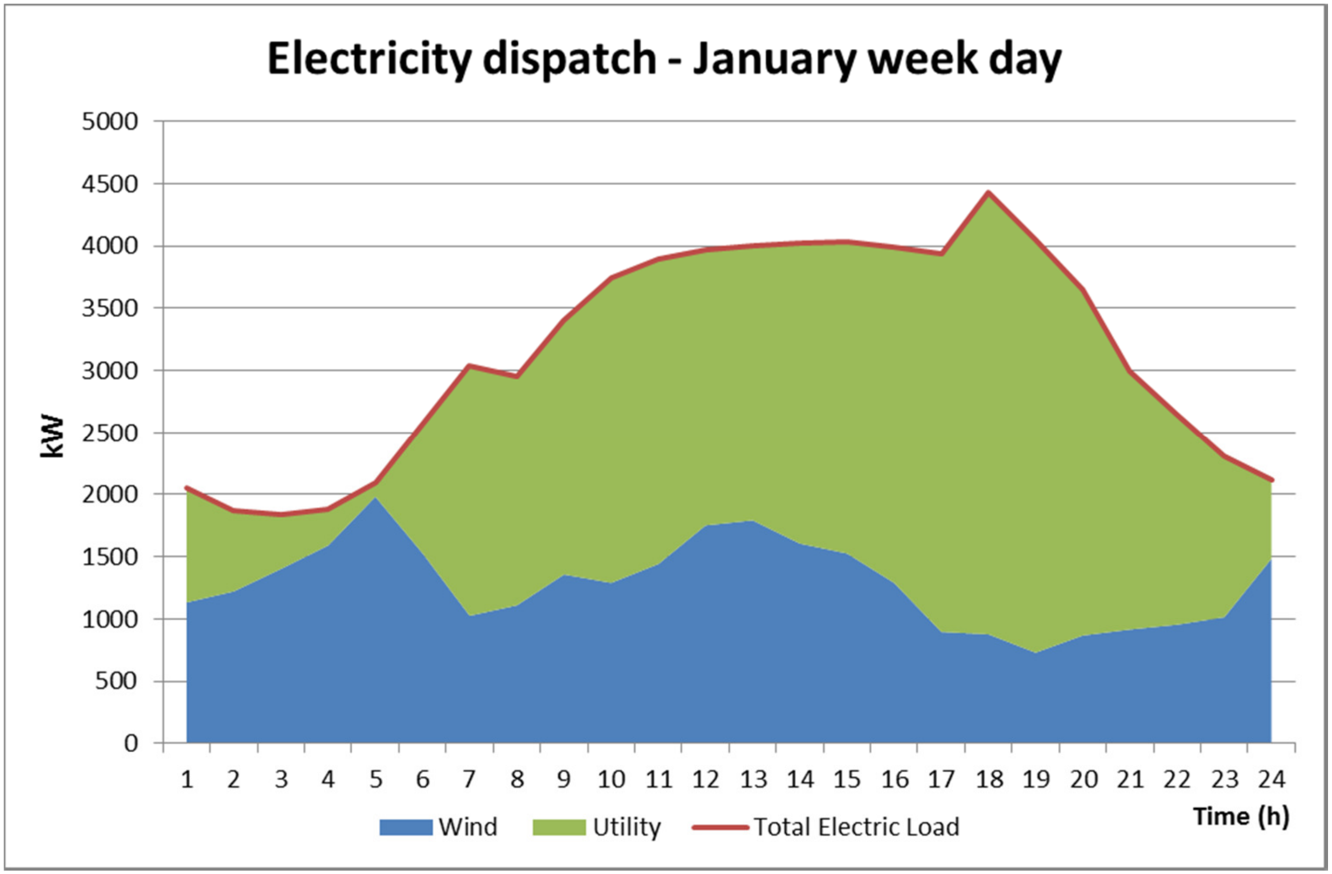
<u>energy output</u>: raw wind data → processing of wind / power calculations

month	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	5.84	6.30	7.23	8.20	10.22	7.88	5.29	5.72	7.00	6.65	7.43	9.03	9.24	8.28	7.87	6.65	4.62	4.52	3.76	4.47	4.72	4.92	5.23	7.65
2	9.86	10.24	10.93	7.43	6.37	5.17	6.02	6.70	4.96	5.46	7.01	7.97	7.91	9.00	8.23	7.82	7.32	6.88	6.51	5.81	5.23	6.52	8.35	10.17
3	19.72	20.33	18.97	17.22	14.31	12.09	12.16	13.64	14.99	14.28	13.77	14.46	13.77	13.07	11.83	11.59	10.25	9.51	10.14	10.27	13.27	14.50	17.48	20.01
4	14.27	12.49	9.87	10.21	8.93	9.55	8.87	7.05	7.29	7.62	7.11	6.55	5.99	5.38	7.82	6.82	4.80	5.88	7.32	8.38	9.41	13.05	15.14	18.01
5	12.30	12.73	10.80	8.21	7.14	7.38	7.12	5.96	4.69	3.50	3.02	2.50	2.07	2.50	3.05	2.81	2.92	4.27	4.67	5.21	5.70	6.91	9.00	12.45
6	11.73	10.83	9.51	9.09	9.09	9.14	8.97	7.51	7.72	7.33	5.04	4.21	3.43	2.97	1.92	1.29	1.30	1.48	2.23	2.33	2.86	4.13	6.61	13.10
7	13.19	11.47	11.73	13.47	13.05	11.77	11.20	9.49	7.74	6.20	4.72	2.89	2.19	1.62	1.33	0.63	1.23	2.15	3.01	3.82	4.55	5.51	7.62	11.68
8	8.75	7.54	6.60	6.69	5.63	4.32	4.35	3.69	3.03	2.10	1.98	1.66	1.54	1.41	1.06	0.78	0.67	0.69	0.92	1.34	1.82	2.31	4.02	6.77
9	6.97	6.30	6.58	5.03	4.17	4.09	4.03	3.02	2.18	1.33	0.93	0.48	1.02	1.31	1.63	1.85	1.96	3.36	4.13	4.73	4.68	4.15	4.95	7.76
10	9.04	6.87	7.33	5.97	5.23	5.21	3.76	2.89	2.00	2.01	1.95	2.05	2.29	1.97	1.85	1.95	1.83	1.23	1.73	2.30	2.64	2.35	3.32	6.01
11	7.35	8.04	6.73	7.07	5.88	4.30	4.30	2.99	3.20	2.63	1.97	1.98	1.03	0.94	0.82	0.99	1.35	2.32	2.82	3.45	3.47	3.47	4.38	7.21
12	7.26	6.54	5.73	7.69	6.82	7.26	5.96	6.53	6.29	6.16	5.21	5.33	5.46	4.69	5.11	6.51	6.91	7.96	7.65	7.95	8.96	9.37	8.94	9.13

<u>energy output</u>: processing of raw wind data → wind / power calculations

month	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	1.6	1.6	2.2	2.2	3.0	1.5	1.0	0.6	0.8	1.0	1.3	1.5	1.8	1.7	1.4	0.9	0.0	0.0	0.0	0.0	0.2	0.3	1.1	1.8
2	9.4	7.2	5.3	1.6	0.8	0.0	0.1	0.3	0.0	0.0	0.3	0.6	0.6	1.2	1.1	1.0	0.8	0.8	1.0	1.4	1.8	2.8	3.9	7.7
3	15.2	17.4	16.2	12.8	9.8	6.7	6.7	8.4	9.7	9.8	8.1	7.8	7.2	7.4	6.2	5.0	1.9	1.8	3.9	5.4	8.0	9.6	12.6	15.1
4	11.8	9.4	7.1	6.2	4.9	5.4	3.6	1.8	1.8	1.5	0.9	0.5	0.6	0.5	1.2	0.7	0.4	1.2	1.9	3.2	4.7	8.5	11.0	15.5
5	10.1	10.8	7.8	5.3	3.5	2.7	2.2	1.7	1.1	0.3	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.6	0.9	1.5	2.2	4.8	8.9
6	8.8	7.8	7.2	6.5	5.3	5.2	5.5	3.8	2.6	1.9	1.0	0.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.7	1.6	4.6	10.2
7	11.6	9.4	8.9	11.0	10.6	8.9	7.8	6.4	4.9	3.0	1.8	0.8	0.5	0.0	0.0	0.0	0.0	0.2	0.8	1.2	1.6	2.3	4.9	9.9
8	6.1	5.5	4.5	4.1	1.9	1.3	1.1	0.9	0.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.3	0.7	1.5	3.0
9	3.5	2.2	1.6	0.5	0.1	0.2	0.4	0.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.3	0.4	0.5	1.3	3.9
10	5.6	2.9	1.9	1.2	0.8	0.6	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.3	0.0	0.7	2.2
11	1.8	2.0	1.1	1.0	0.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.3	1.4
12	4.2	2.2	1.0	0.6	0.2	0.4	0.4	0.9	0.4	0.1	0.0	0.0	0.0	0.0	0.1	0.4	0.7	0.9	0.4	0.7	1.5	2.7	3.6	4.6

Test Results for Large College Building



wind power first results

- wind turbines are not cost-effective without subsidies or incentives
- wind power can provide a significant part of the total load
- unpredictability of wind speed requires coupling with energy storage
- the current representation of time in DER-CAM introduces significant limitations in wind power modeling
- possible need to increase time resolution and/or add higher number of representative days

Feature

Improved Modeling of Thermodynamics in Buildings: Electrochromic Windows

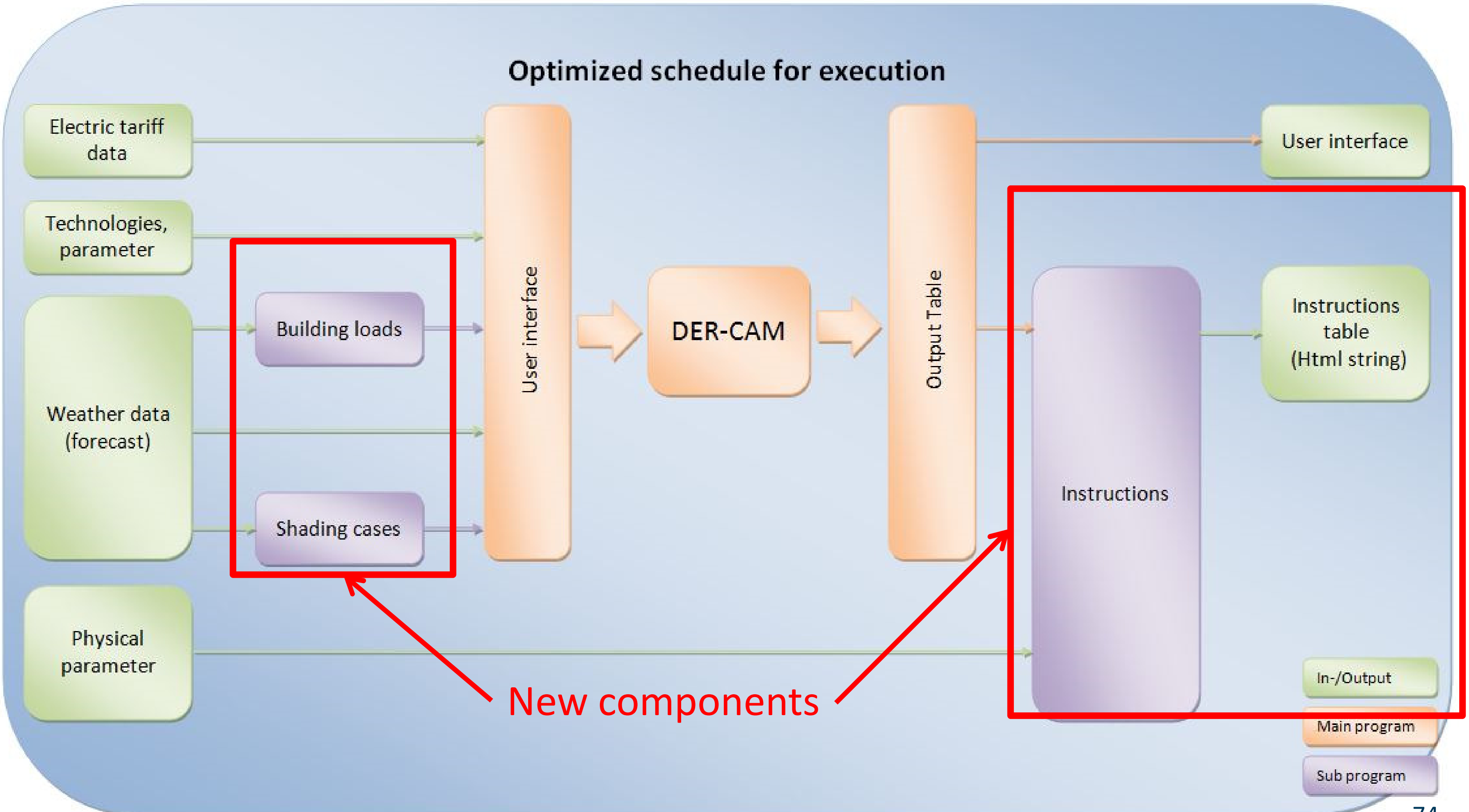
- Electrochromic (EC) windows are a type of shading system. EC provide different levels of shading with a small electricity consumption required for the switching process (0.5Wh/m^2, 5V), which can be used to control building cooling loads.
- trade-off: increased levels of shading reduce cooling loads, but increase lighting loads.

→ **optimization problem**

Shading

- DER-CAM will support variable shading (EC windows, shutters) in the Operations version
- user is required to input load changes (electrical and cooling) for different shading levels
- requires pre-processing of environmental conditions for shading levels (lookup table) and building loads (E+)
- DER-CAM finds optimal shading levels for each time step (down to 5 min)

Shading


Optimized schedule for execution
Electric tariff data
Technologies, parameter
Weather data (forecast)
Physical parameter
Building loads
Shading cases
User interface
DER-CAM
Output Table
User interface
Instructions
Instructions table (Html string)
New components
In-/Output
Main program
Sub program

DER-CAM DECISION SUPPORT TOOL FOR DECENTRALIZED ENERGY SYSTEMS

ANALYTICS | PLANNING | OPERATIONS

applications

- evaluate technical potential
- run optimization for possible buildings in China (China Energy Group at LBNL)

status

- most of programming completed

Feature

Multi-Year Optimization

challenges:

- microgrids are often modular
- investment decisions over the years are influenced by trends both in energy demand and technology costs
- technology degradation over time must be considered
- find optimal investment and re-investment years over the multi-year period

improvements in multi-year optimization:

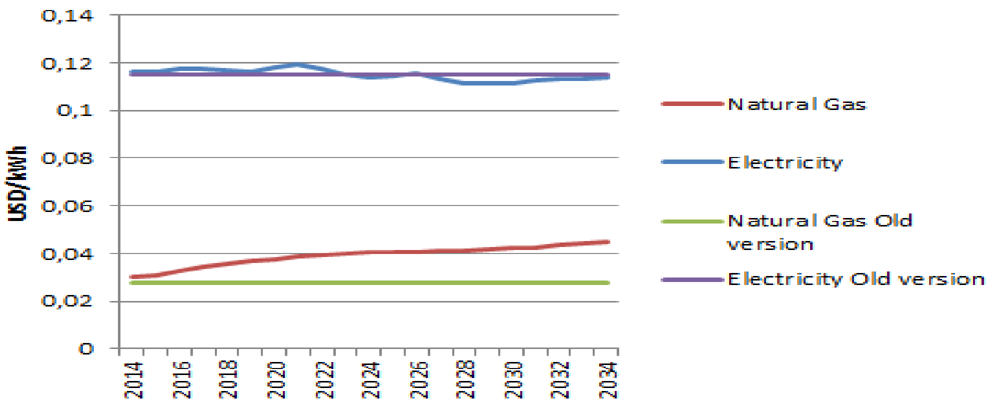
- load variability
- fuel cost changes
- technology degradation
- changing tariffs
- changing taxes
- changing weather data

DER-CAM DECISION SUPPORT TOOL FOR DECENTRALIZED ENERGY SYSTEMS

ANALYTICS | PLANNING | OPERATIONS

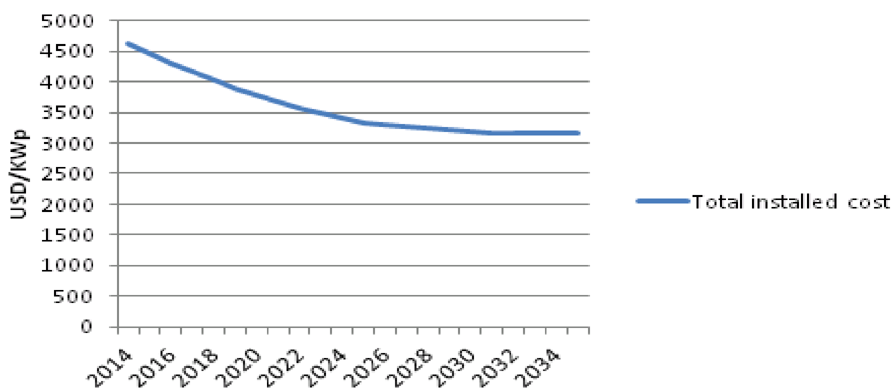
application: office building in San Francisco

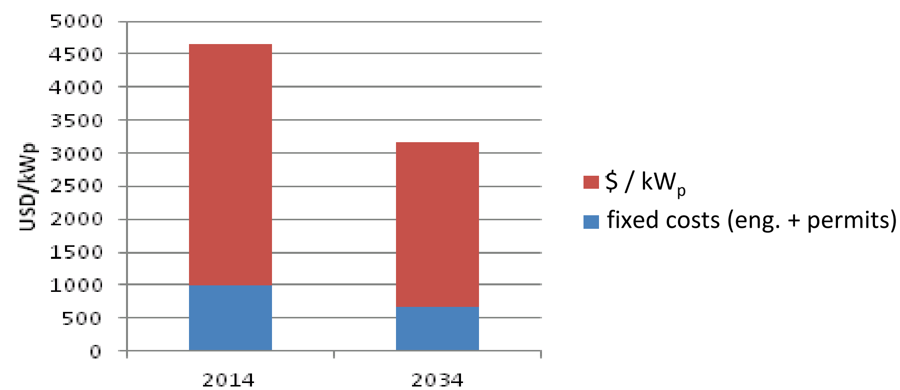
Fuel Costs



[Annual Energy Outlook, EiA 2013]

PV Capital Cost forecast





DER-CAM DECISION SUPPORT TOOL FOR DECENTRALIZED ENERGY SYSTEMS

ANALYTICS | PLANNING | OPERATIONS

investment plan

Installed Technologies	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032	2033
0% PV Degradation																				
PV 0% degradation						Still running...														
Discrete Technologies																				
> CHP																				
Batteries																				
0.5% PV Degradation																				
Installed Capacity, PV 0.5% degradation								(497.13kW) 0.50% degradation												(467.3kW)
Discrete Technologies	(500kW)																			
> CHP	(250kW)																			
Batteries	No Adaptation																			
0.75% PV Degradation																				
Installed Capacity, PV 0.75% degradation											(498.45kW) 0.75% degradation									(464.81kW)
Discrete Technologies	(500kW)																			
> CHP	(250kW)																			
Batteries	No Adaptation																			
1% PV Degradation																				
Installed Capacity, PV 1% degradation						Still running...														
Discrete Technologies																				
> CHP																				
Batteries																				
Old Run-set																				
Installed Technologies	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032	2033
PV							No Ad.										No Ad.			
Discrete Technologies							250kW										800kW			
> CHP							250kW										800kW			
Batteries							145kWh										No Ad.			

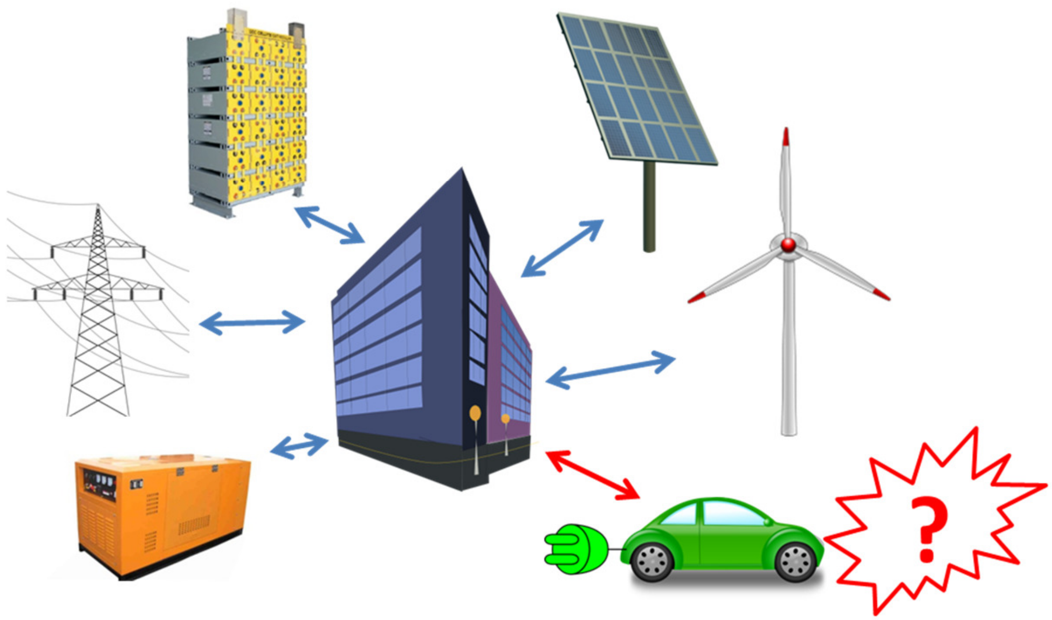
Feature

EV Modelling

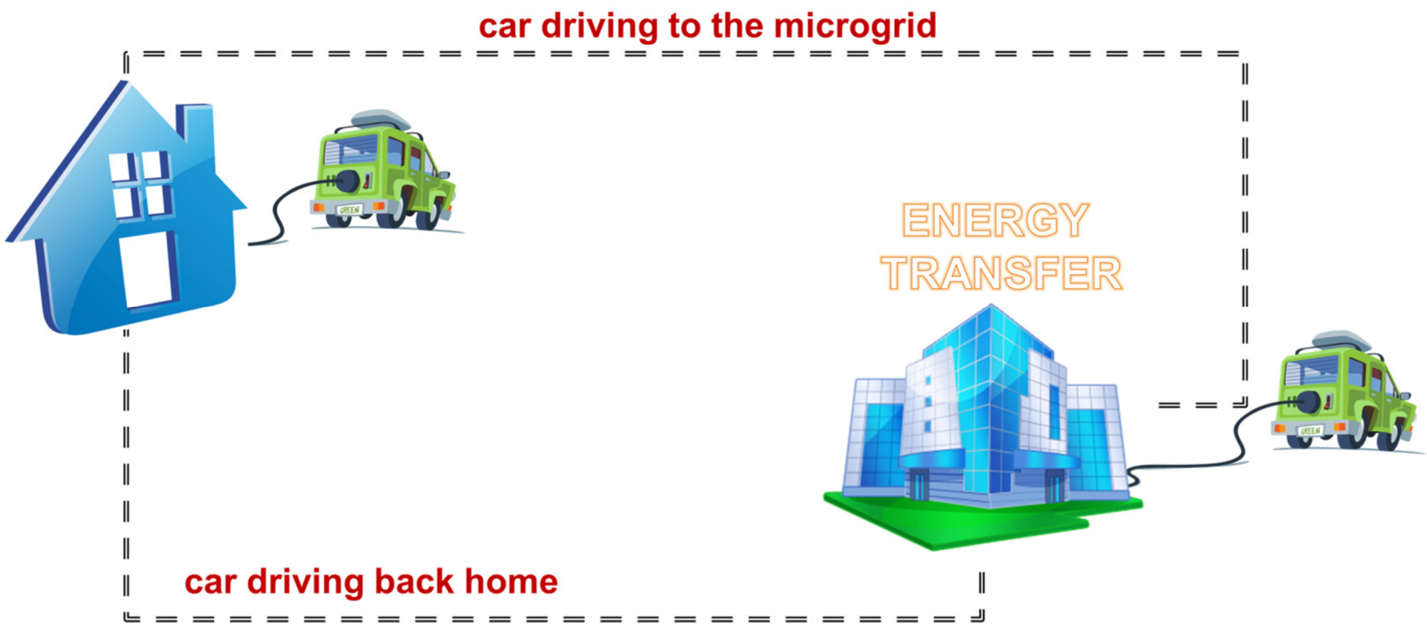
EVs in DER-CAM

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

Impact on optimal DER investment decisions



EVs in DER-CAM



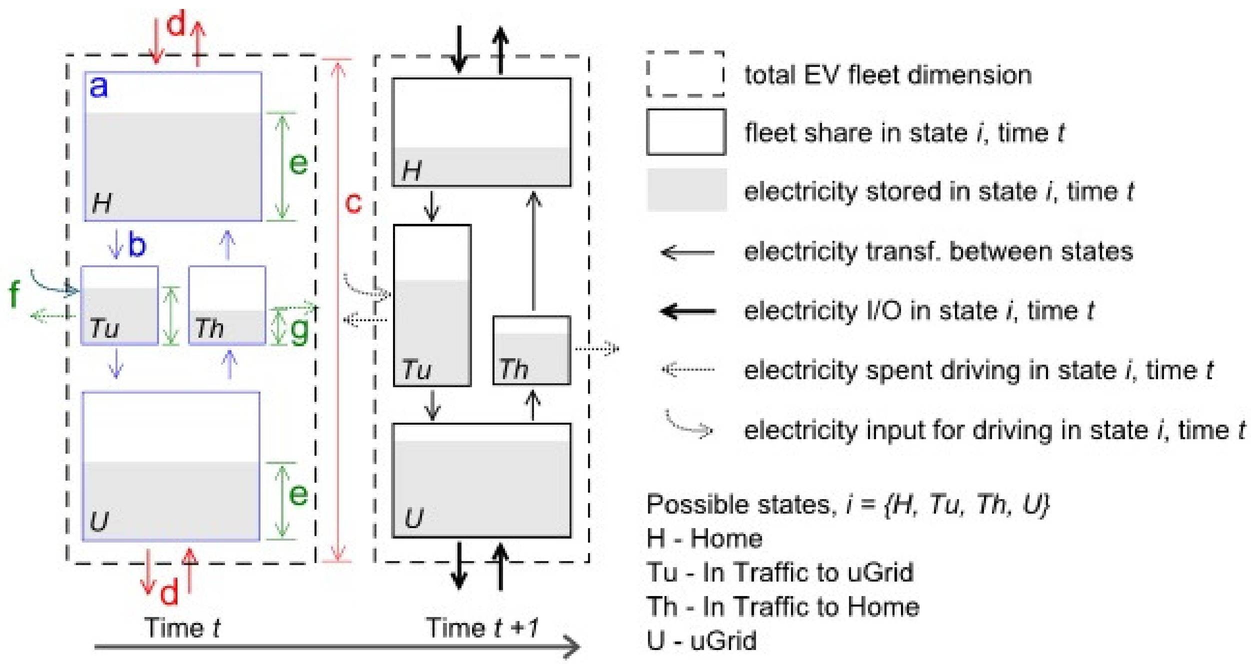
optimization determines the energy flow direction, microgrid could perform load management

EV Fleet Aggregator

Key assumptions:

- microgrid costs: charging infrastructure ($1000/car), energy use and battery degradation
- EV owner purchases car anyway and has no disadvantage due to microgrid
- all benefits and inefficiencies are allocated to the microgrid
- all cars charge at least enough electricity at home for a daily roundtrip (not included in microgrid costs)
- driving electricity can be used by the microgrid but must be returned
- when cars change state, the SOC is equal to the average SOC of the fleet in the original state, plus electricity needed for driving

EV Fleet Aggregator



Parameters

a) fleet distribution
b) fleet transitions

Key decision variables

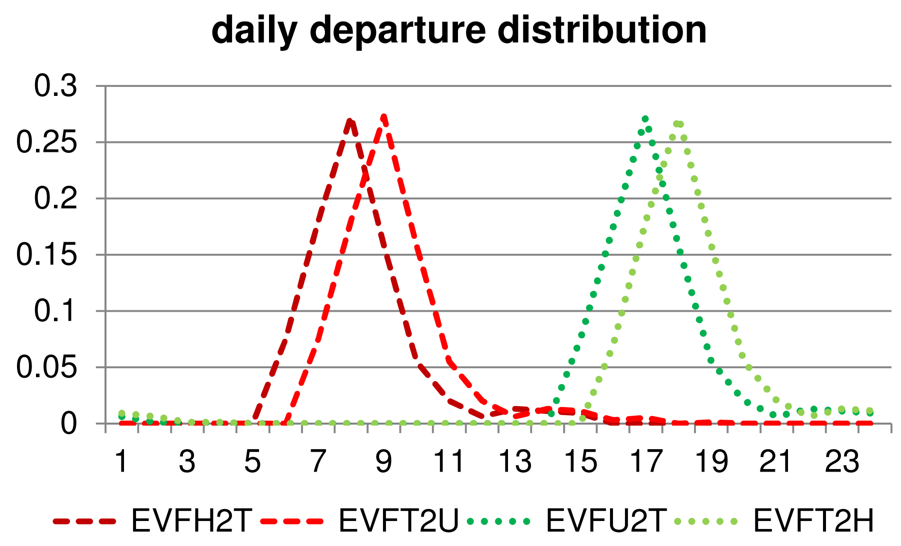
c) EV fleet size
d) electric input / output at home and uGrid

Other variables

e) electricity stored at home and uGrid
f) driving consumption
g) electricity stored in traffic

Case Study - Source of Uncertainty

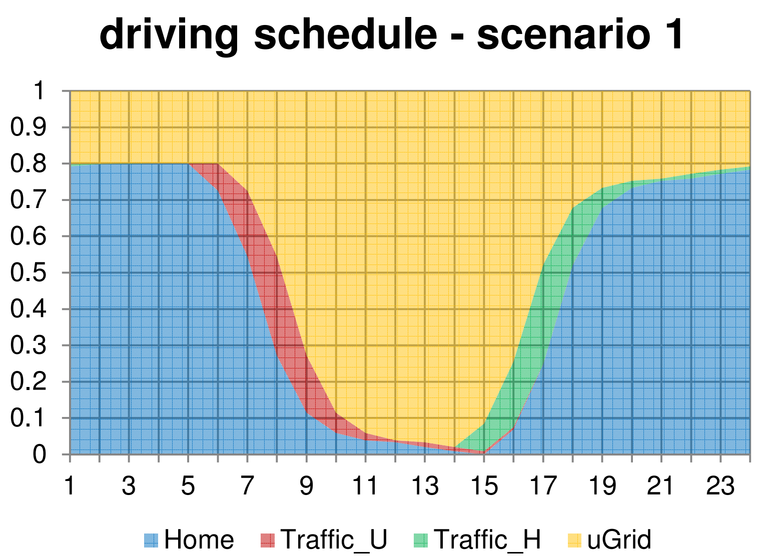
EV fleet distribution obtained from a 2009 US survey on departure times for daily commute round trips [1]

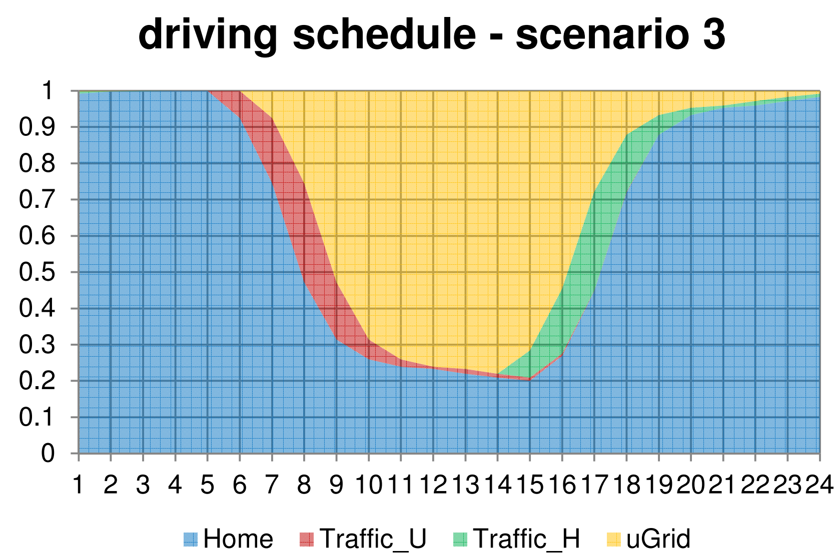


[1] *Source*: B. Mckenzie and M. Rapino, "Commuting in the United States : 2009, American Community Survey Reports, ACS-15.," Washington, DC, 2011

Case Study - Source of Uncertainty

driving scenarios obtained by maximizing time at the uGrid (S1), at home (S3) and using the average (S2)





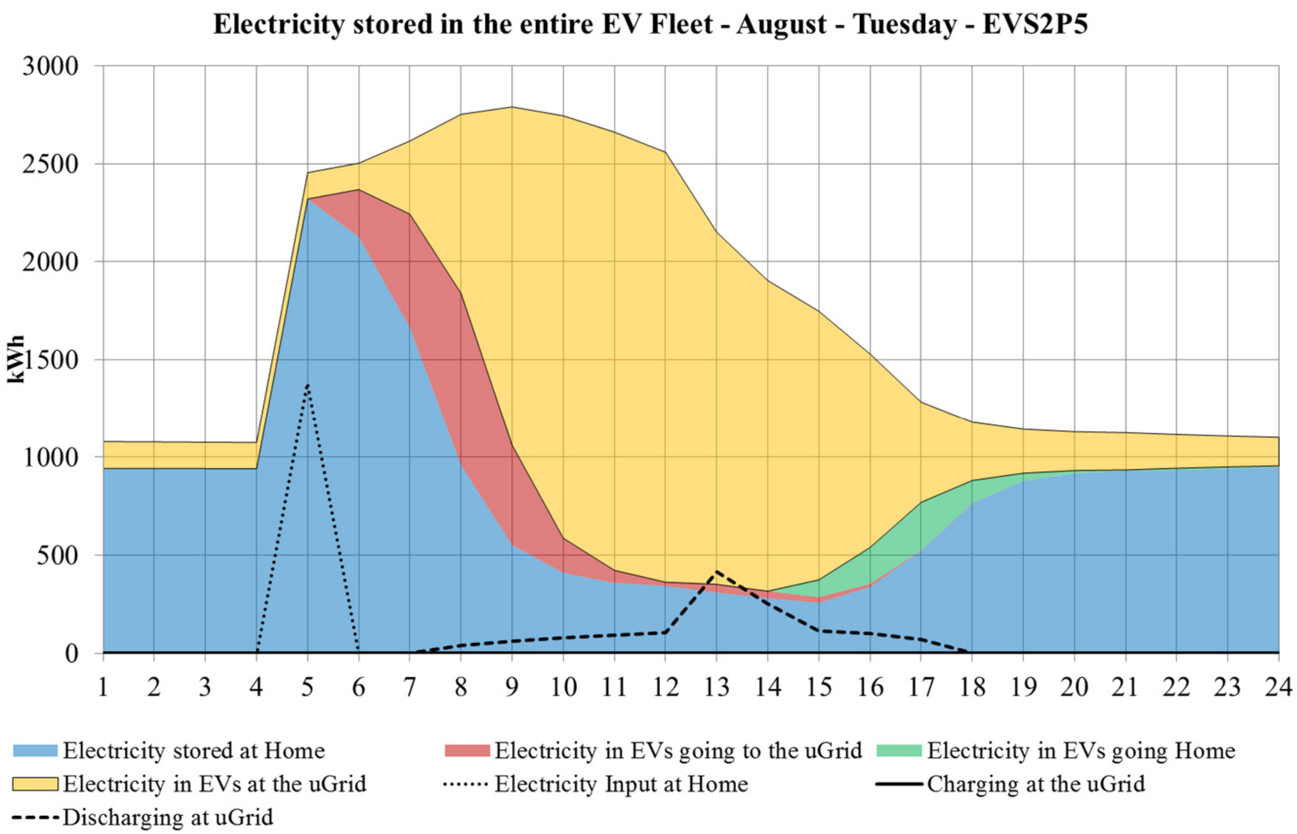
Case Study

- Medium office building in San Francisco
- 380 kW 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 for DER investments: 5 and 12 years

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 at home

DER-CAM DECISION SUPPORT TOOL FOR DECENTRALIZED ENERGY SYSTEMS

ANALYTICS | PLANNING | OPERATIONS

Case Study – Key Results

Case Refs.	Optimality gap (%)	Total Energy Costs ($)	Total CO_2 (kg CO_2)	Optimal Capacity (kW/kWh)				
				PV	ST	ICE /HX	ES	EV (cars)
BAU	0	281,286	1,017,475	-	-	-	-	-
EVSTP5	0	269,293	1,053,325	-	50.9	-	-	3,578(2)
NOEVP12	0.091	269,530	737,856	189.9	-	60	-	-
EVS1P12	0.029	264,135	769,530	191.1	-	60	-	2,804
EVS2P12	0.057	265,257	758,197	192.3	-	60	-	2,005
EVS3P12	0.062	266,229	754,716	188.4	-	60	-	1,463
EVSTP12	1.087(1)	266,270	823,138	201,1	83,7	-	-	2,423

1) Max optimality gap set to 1%
2) Constrained by maximum parking area

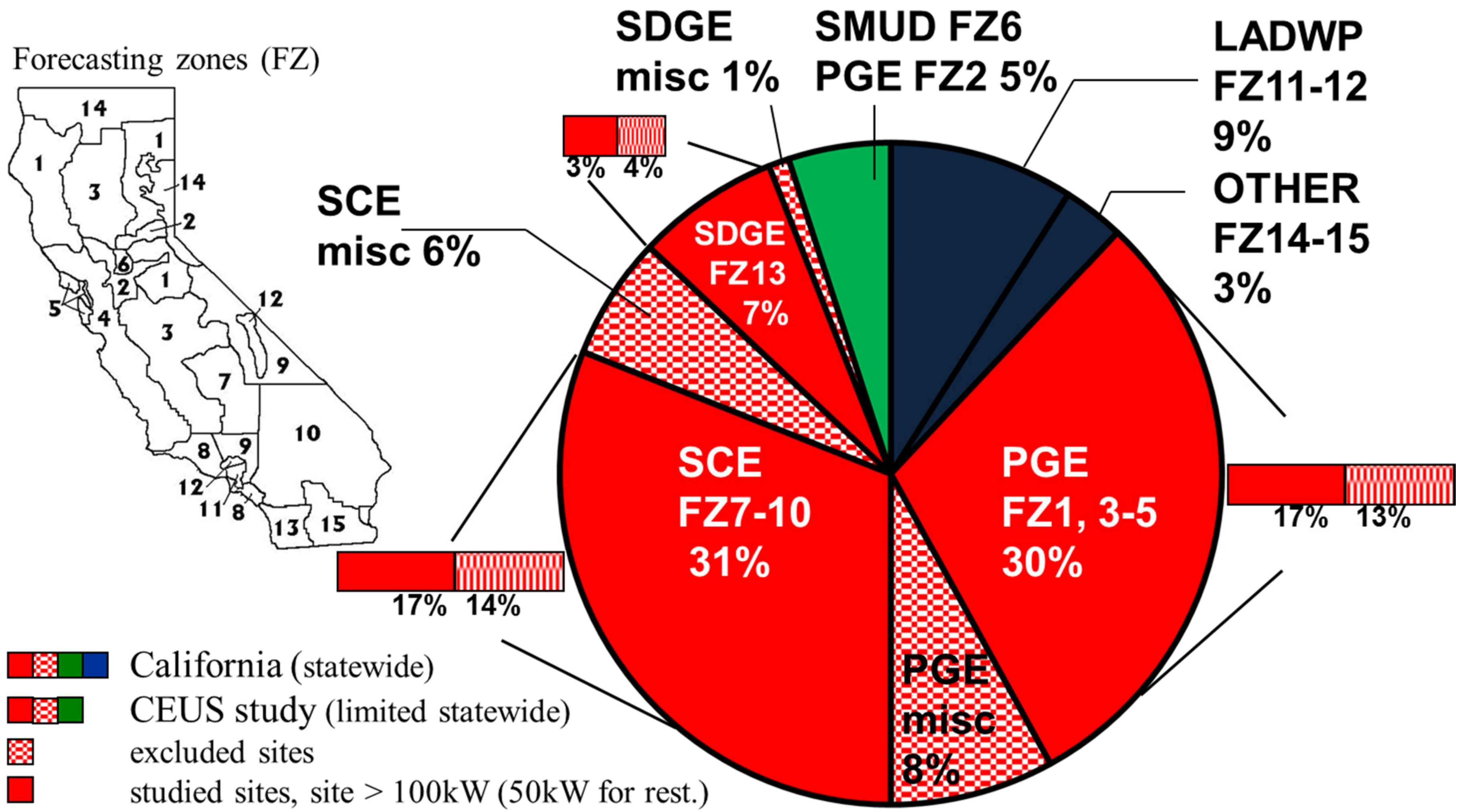
EV Findings

- the introduction of EVs leads to financial savings with both 5 and 12 year payback periods (CO_2 results depend on marginal grid emissions)
- microgrid total energy costs tend to be similar once EVs are allowed in the runs
- solving the stochastic problem leads to the installation of solar thermal panels and higher PV, replacing ICEs (note optimality gap)
- best strategy: EVs are charged at home and used later at the microgrid in order to reduce microgrid energy costs
- impact of uncertainty in driving pattern is limited (Why?)
- next step: consider other sources of uncertainty

Application

CA CHP study

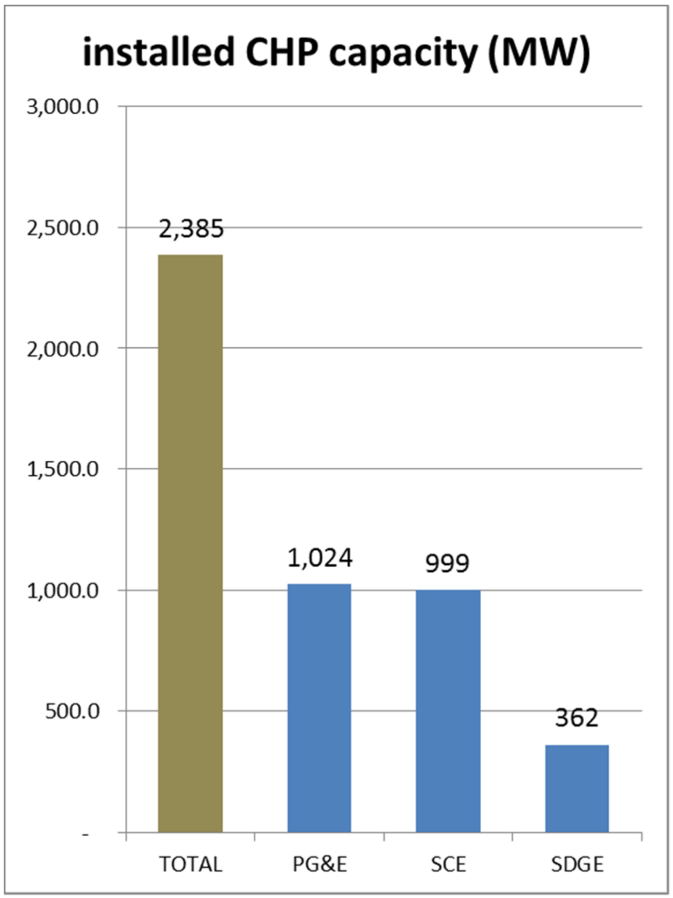
37% of Commercial Electric Demand

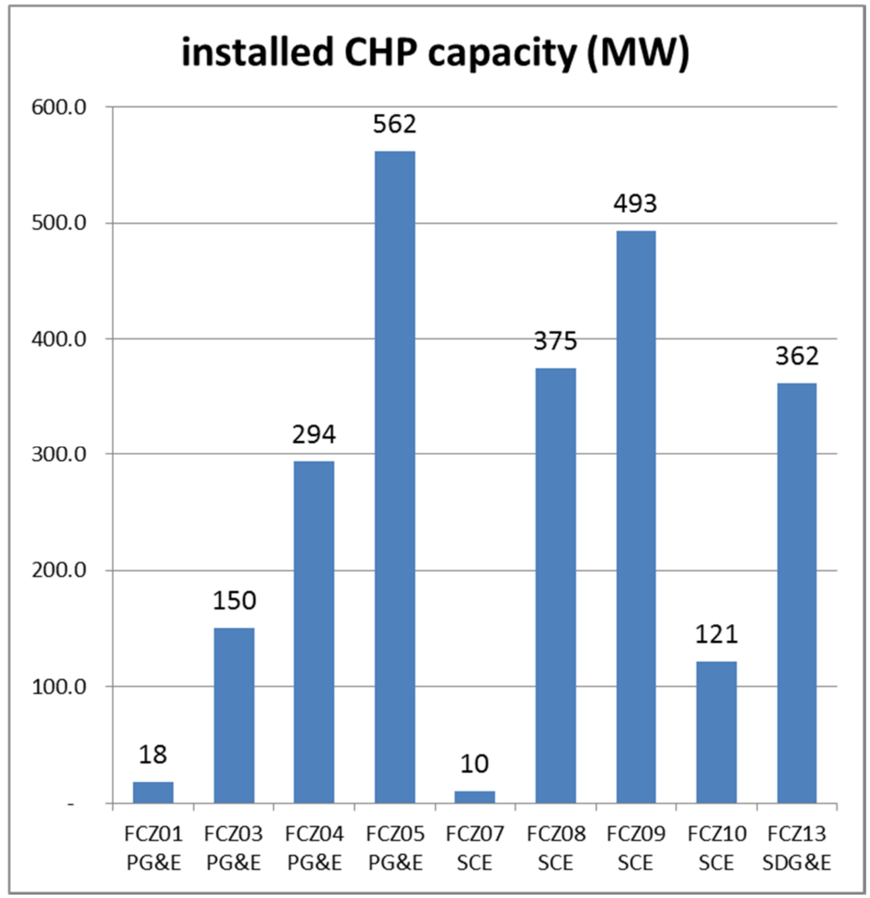


DER-CAM DECISION SUPPORT TOOL FOR DECENTRALIZED ENERGY SYSTEMS

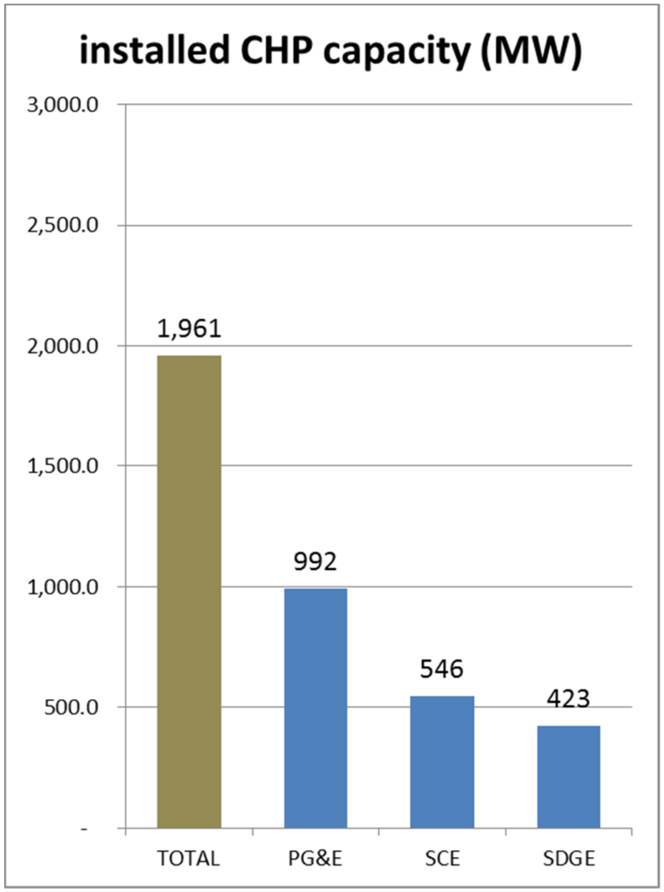
ANALYTICS | PLANNING | OPERATIONS

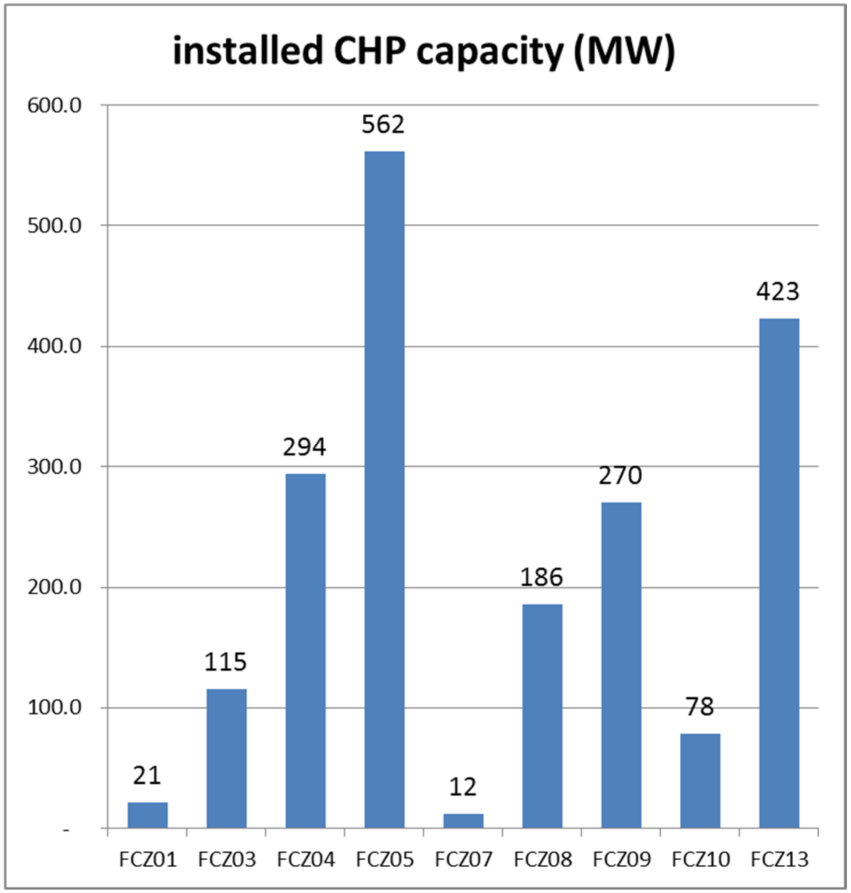
Installed CHP Capacity in 2020





Installed CHP Capacity in 2030





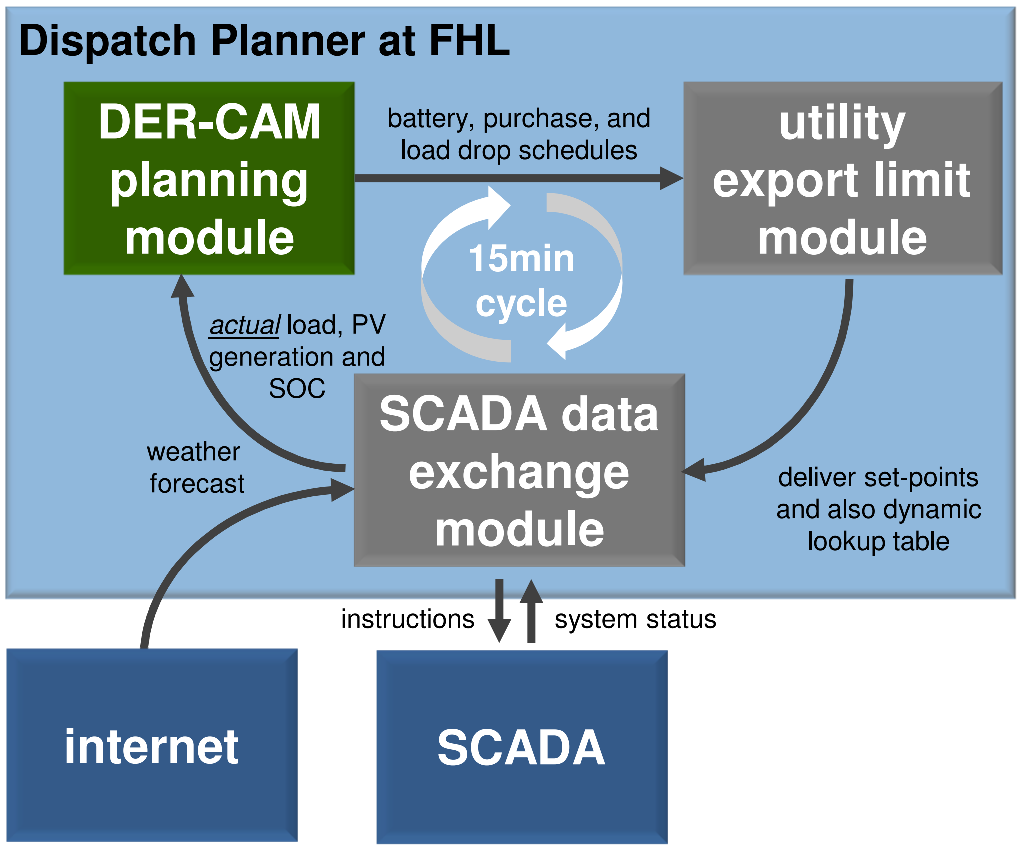
Application

Microgrid Controller at Fort Hunter Liggett (FHL)

Overview FHL

- large 2 MW PV and battery system 1 MWh
- in the future 8 MW of PV and full microgrid
- no supervisory controller available

Current DER-CAM Model at FHL



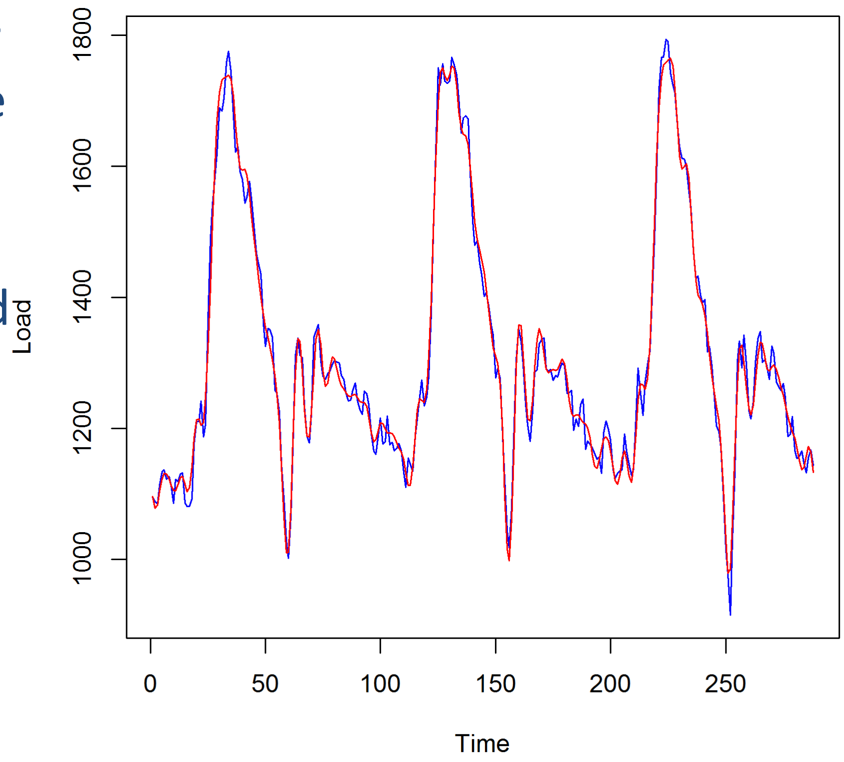
Forecasting Load and PV Generation

For real-time optimization, load and PV generation need to be forecasted for FHL. Both factors are driven by *different influences*.

- load is driven by base occupancy and shows relatively stable daily patterns. Influence of outside temperature appears to be relatively minor.
- PV is driven by solar radiation, which depends on the position of the sun and various seasonal patterns. Patterns can be very volatile due to clouds.
- load data is available in 15-minutes intervals as net load, weather data is available in hourly intervals, PV data varies between 15 minutes and hourly

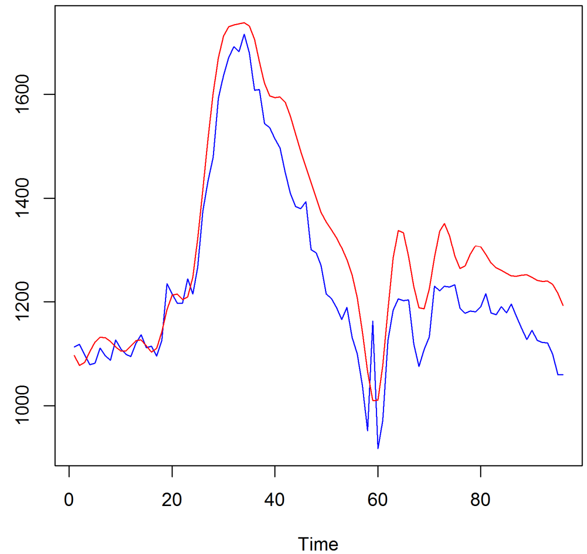
Forecasting Load

- load shows consistent patterns for each day of the week (holidays are similar to Sundays)
- to forecast next Tuesday, the past three Tuesdays are considered and a Fast Fourier Transformation (FFT) is used to extract the most important frequencies
- the resulting curve contains the main pattern without noise



Forecasting Load

average error over a day is around 10%

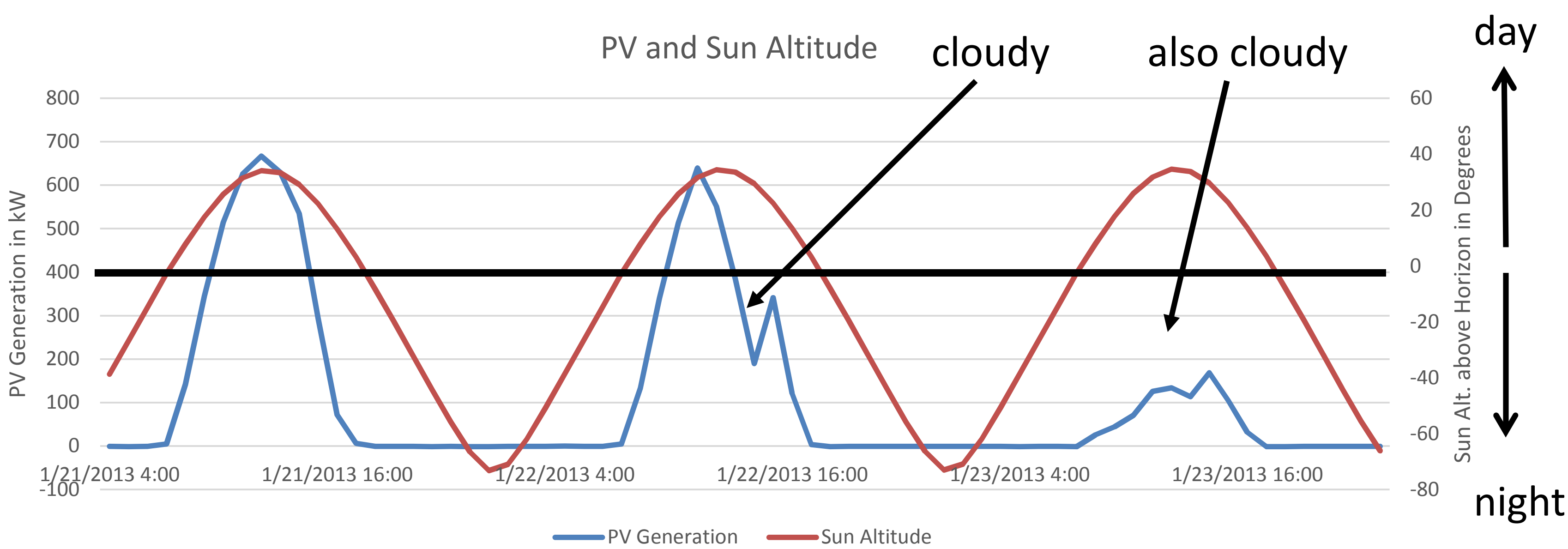


- 😐 change in base occupancy is only slowly incorporated by FFT
- ☺ forecasted values are multiplied with a parameter ***d*** that starts out at 1 and decreases / increases whenever deviations between forecasted and actual values exceed a certain threshold

Forecasting PV

Weather forecast data is available hourly and difficult to interpolate (qualitative data like “cloudy”).

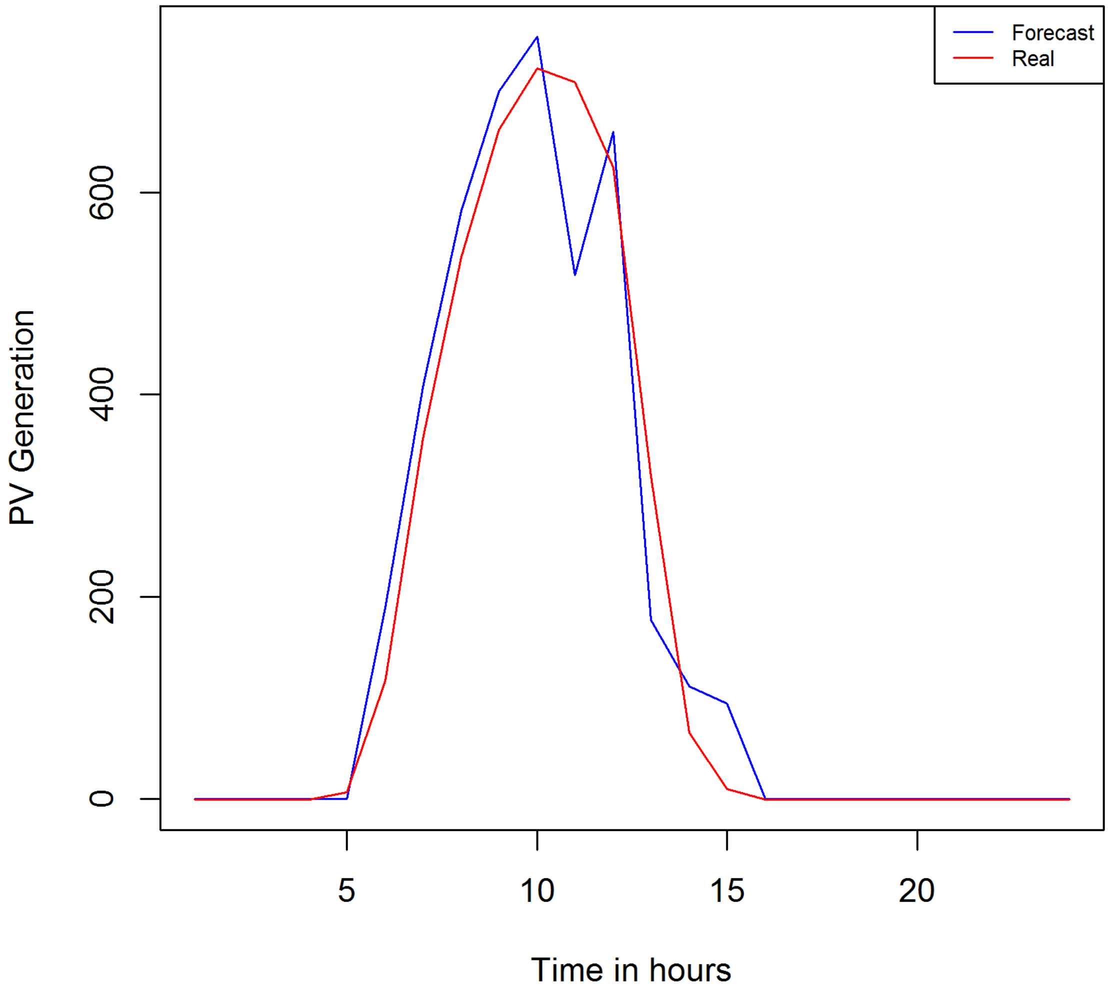
- solar radiation depends on position of sun and seasonal factors
- in the short term, these seasonal factors are fixed and sun altitude becomes dominant influence of clear-sky PV generation



Forecasting PV

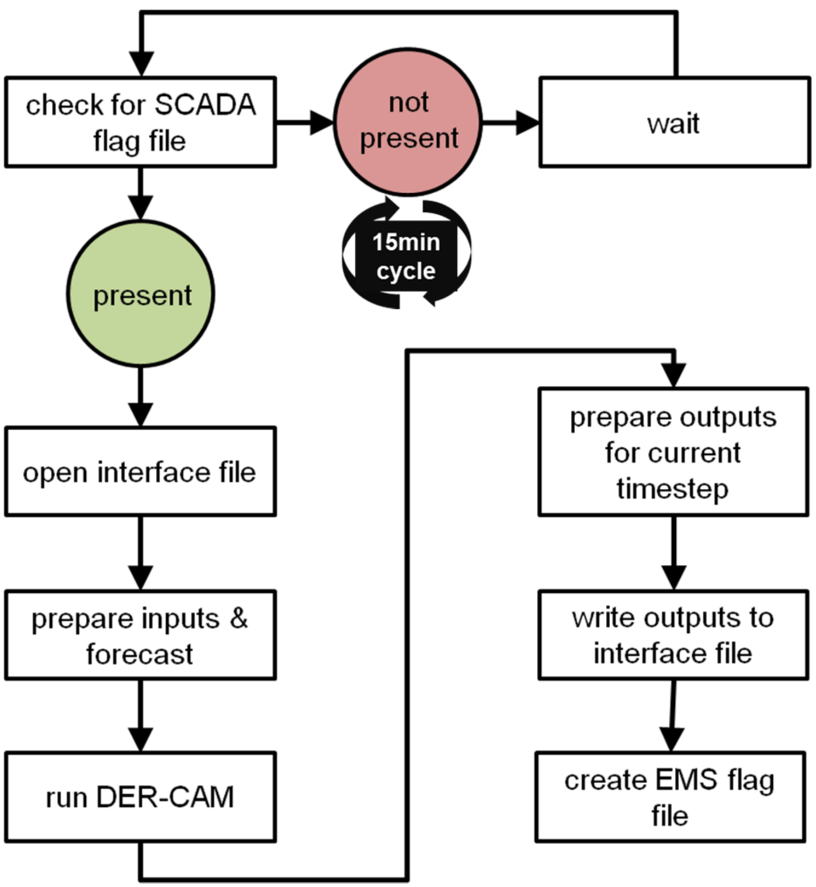
- clear-sky PV generation is forecasted using a simple linear model that relates sun altitude to power generated of the past 30 clear-sky hours
- for fog, haze, and clouds clear-sky PV generation is modified by a specific factor to get expected generation
- deviation (i.e. (forecast-real)/real) is less than 5% in 80% of the cases and less than 10% in 90% of the cases
- forecast errors mainly due to inaccuracies in qualitative data ("03 PM overcast" does not necessarily imply that it is overcast for the entire hour)

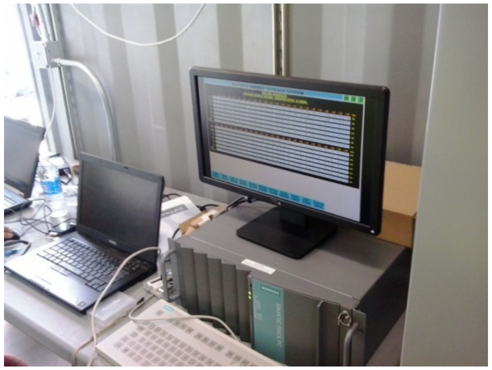
Forecasting PV

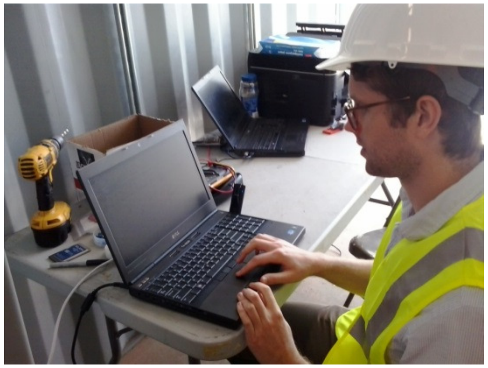


SCADA interface

early development stages achieved successful feeding of Operations DER-CAM dispatches in the FHL SCADA system

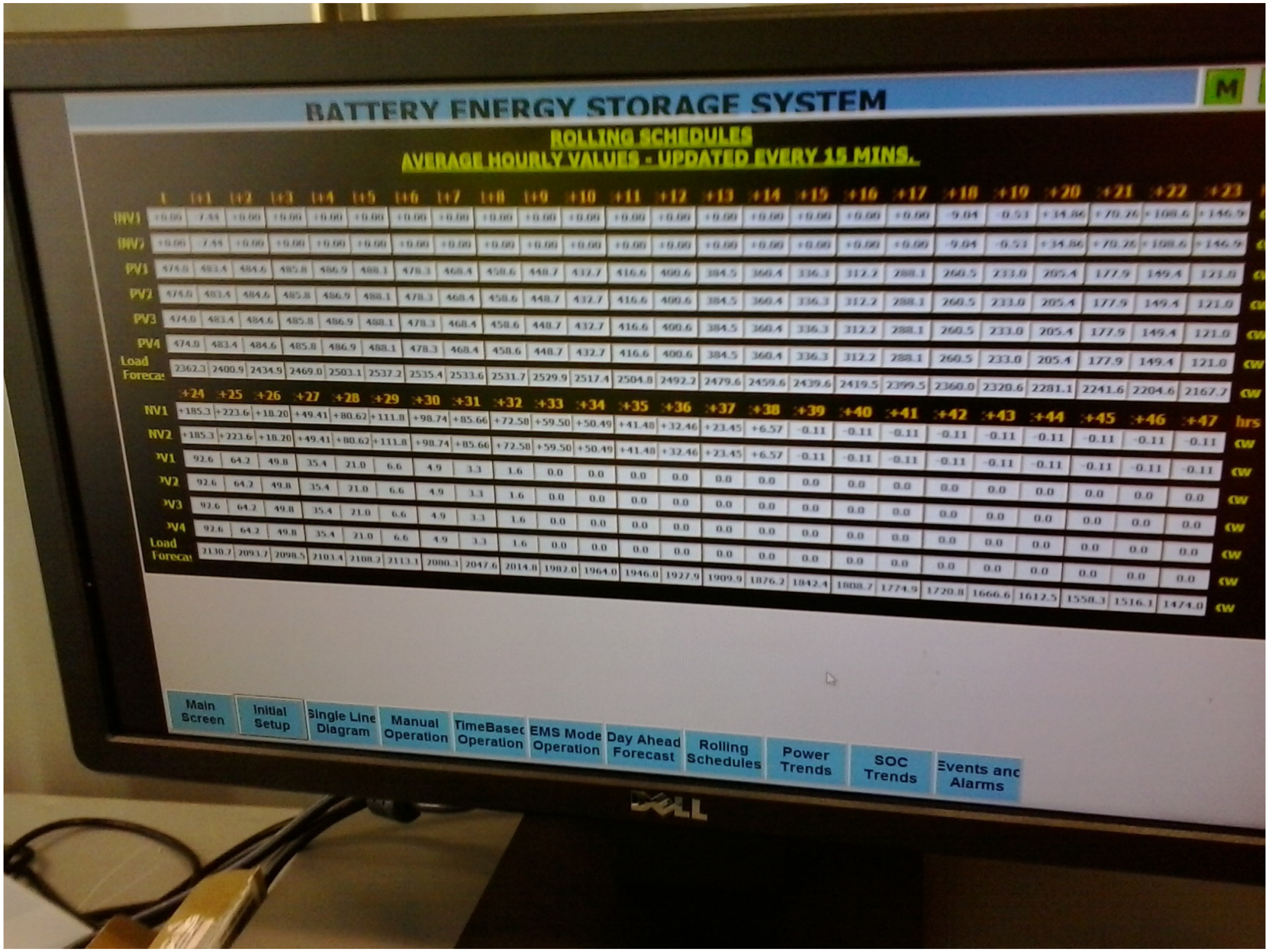






SCADA Interface

BERKELEY LAB
Lawrence Berkeley National Laboratory



DER-CAM Output: Example