University of Colorado **Boulder**

Assessing Impact of Large-Scale Distributed Residential HVAC Control Optimization on Electricity Grid Operation and Renewable Energy Integration

May 11, 2015

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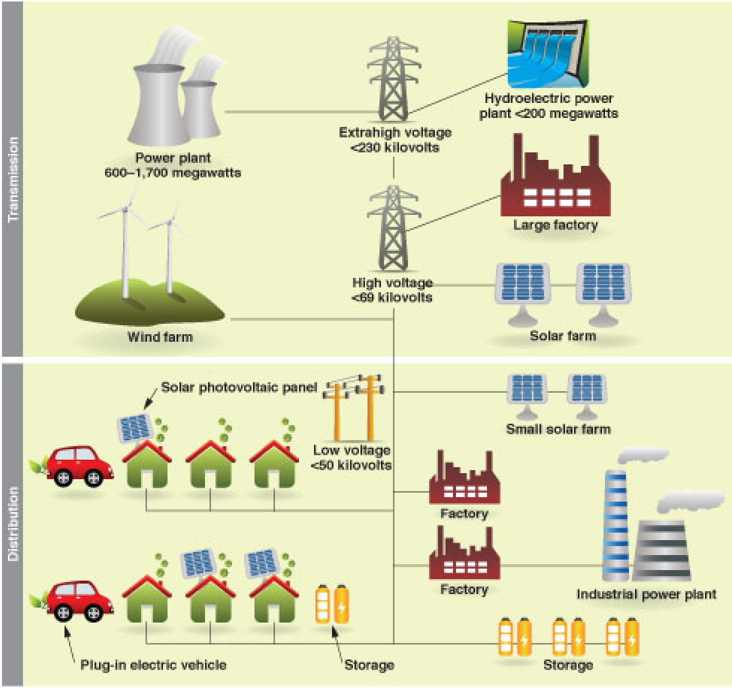

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OUTLINE

1. Introduction
2. Methodology
3. Studies
4. Conclusions

INTRODUCTION

BACKGROUND

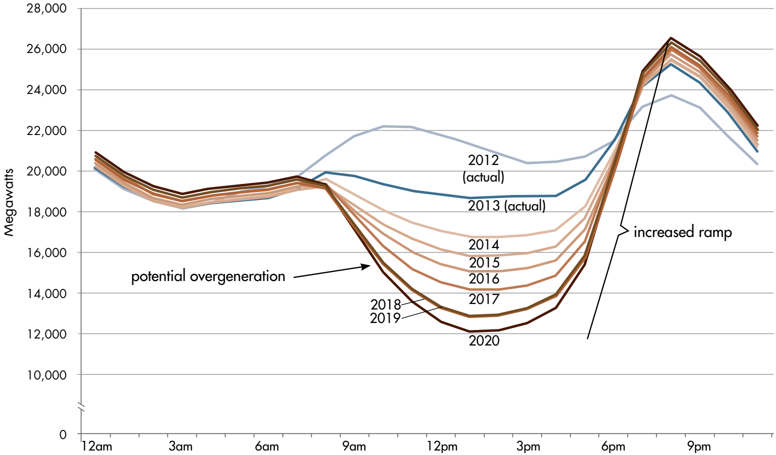
According to United States Energy Information Administration:

- Residential electricity use has been rising for over sixty years at a rate of 20 TWh per year.
- Corresponds to an increase in residential air conditioning, from 57% in 1980 to 87% in 2009.
- It is estimated that residential air conditioning exceeds 293 TWh annually.

Over the next 25 years:

- Total electricity used by the residential sector will increase over the next 25 years.
- Residential electricity use by air conditioning will increase 24% (to 363 TWh).
- Roughly 48 GW capacity will need to be added to satisfy summer peak demand.

MOTIVATION



http://www.caiso.com/

Figure: The ``Duck Curve'' showing overproduction by PV and increased ramping

GUIDING HYPOTHESES

» Model predictive control (MPC) for residential HVAC control may eliminate traditional DR.

» Short-term predictive control of residential loads allows demand flexibility and graceful response under grid stress events.

» Widespread adoption of residential MPC offers the promise of deeper penetration of renewable energy without destabilizing electric grid operations.

RESEARCH QUESTIONS

» How should distributed HVAC MPC be performed? Is this a template for real-world implementation?

» What driving function should be supplied to create desired aggregate demand response?

» Can distributed MPC be used for day-ahead resource planning?

» Would distributed MPC allow a higher penetration of renewable energy to be utilized?

METHODOLOGY

OUTLINE

OVERVIEW

Combine

- Fast, reduced order building model (1000+)
- Distribution feeder models (3 locations)
- Power flow simulation software (GridLAB-D)
- Distributed but **directed** model predictive control scheme

To evaluate MPC of residential thermostats

- Demand reduction & load shaping
- In areas with high rooftop solar penetration
- To `absorb' variability introduced by wind

BUILDING MODEL

HVAC AND CONTROLS

HVAC models from ASHRAE Toolkit 2 and EnergyPlus

» Direct expansion AC/HP
» Constant efficiency gas furnace
» lots more...

Realistic thermostat model

» Compressor staging
» Set point hysteresis
» Minimum cycle time

HVAC CYCLING

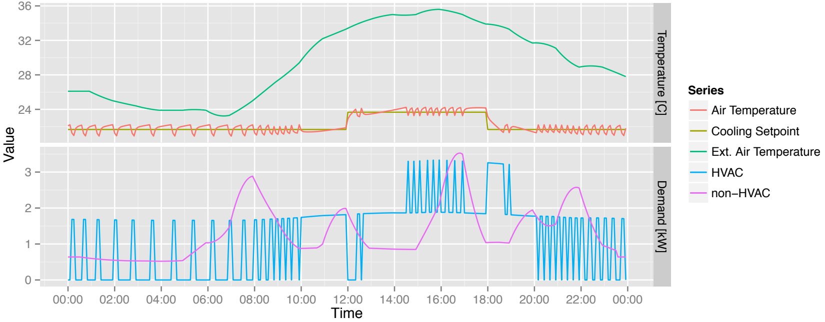


Figure: Example output from reduced order model showing HVAC cycling, thermostat hysteresis, staging and minimum run time. Low cooling set point results in cycling early in the morning and frequent second cooing stage operation in the afternoon.

VALIDATION

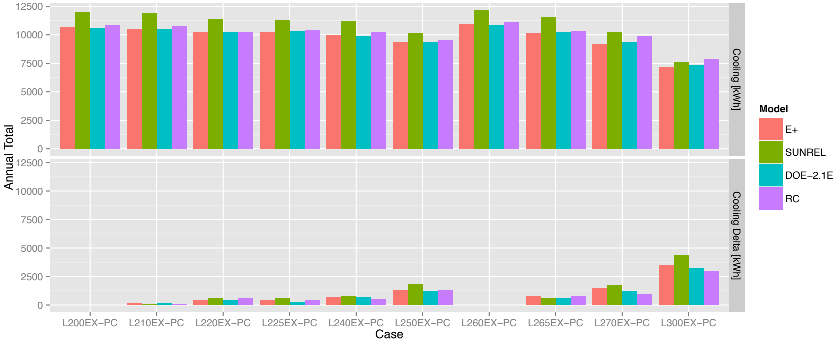


Figure: Comparison of annual electricity use in cooling physics test cases for EnergyPlus, SUNREL, DOE2.1E, and the reduced-order model (BESTEST-EX Cooling).

VALIDATION

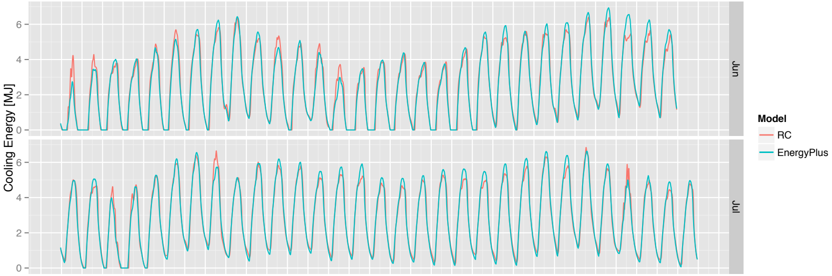


Figure: Cooling load profile calculated by reduced order model compared to EnergyPlus. NRMSE (for all days where cooling is enabled): 5.5%

GRID MODEL

GRID MODEL DESCRIPTION

Distribution system modeled at the feeder level with GridLAB-D

- Models all components of the system from transformers to lines to lights.
- Solves unbalanced power flow for three-phase distribution system.
- Provided with 24 feeder models typical of U.S. systems.

CHARACTERISTICS

Table: Key characteristics of three climates & feeder models studied.

	Houston	Los Angeles	New York
Cooling Degree Days base 50	4043	2674	1911
Cooling Degree Days base 65	1667	343	543
Nominal voltage (kV)	22.9	12.47	12.47
Nominal load (MW)	12	7.8	7.4
Commercial transformers	14	0	6
Industrial transformers	0	0	0
Agricultural transformers	0	107	0
Residential transformers	284	1491	396
Number of residences	2146	1326	1506
Percent of residential consumption	80%	78%	86%
Air conditioning penetration	98%	54%	79%

MODEL HYBRIDIZATION

- RECS sampled to create population of homes.
- Population of homes translated to GridMPC input.
- Electric demand from each building inserted into GLD model as ZIP load:

$$P = \left|\frac{V_a}{V_n}\right|^2 |S_n| Z_{\%} \cos(Z_\theta) + \left|\frac{V_a}{V_n}\right| |S_n| I_{\%} \cos(I_\theta) + |S_n| P_{\%} \cos(P_\theta) \quad (1)$$

$$Q = \left|\frac{V_a}{V_n}\right|^2 |S_n| Z_{\%} \sin(Z_\theta) + \left|\frac{V_a}{V_n}\right| |S_n| I_{\%} \sin(I_\theta) + |S_n| P_{\%} \sin(P_\theta) \quad (2)$$

- ZIP fractions calculated from original GLD model. Assumed to be time invariant.

MONTHLY VALIDATION

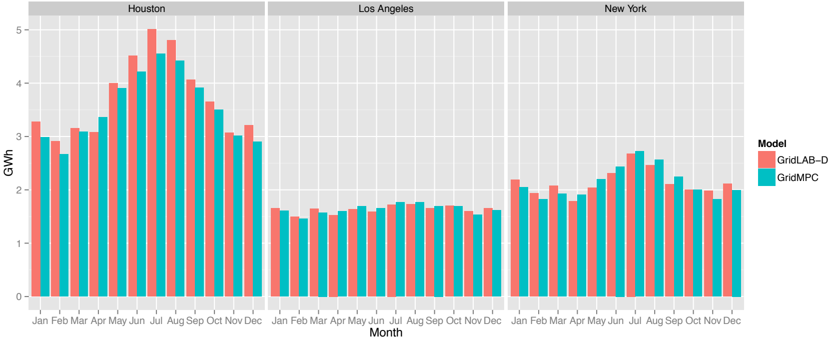


Figure: Monthly validation of hybrid model. Houston annual error -5.0%, Los Angeles annual error 0.2%, New York annual error 0.1%.

SUB-HOURLY VALIDATION

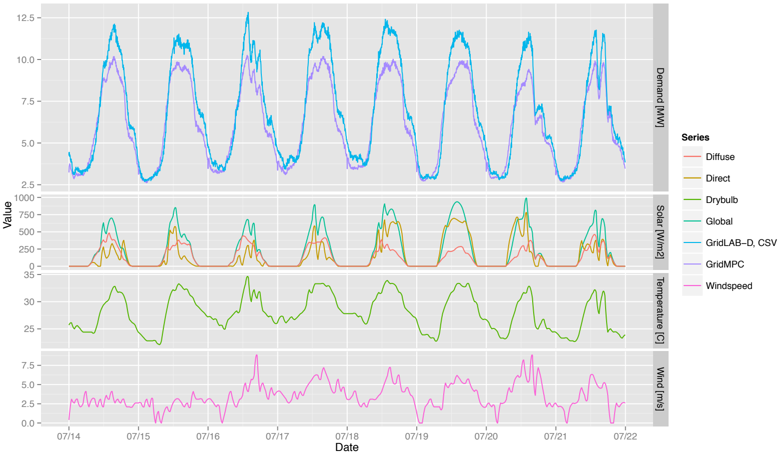


Figure: Demand validation for Houston feeder model. Total annual error -5.0%.

MPC FRAMEWORK

DESCRIPTION

Java framework that integrates

- Reduced order model(s)
- Model predictive controller(s)
- Power flow simulation

Features

- Weather files in EPW or TMY2 format.
- Stateful: Maintains building state across simulations.
- Fast. 1 month optimization, 1500 buildings = 1 hour.

CONTROL SCHEME

Classic receding-horizon optimal control

- Distributed. Model predictive controller in each home.
- Thermostat cooling set point schedule is control vector.
- 48 decision variables (30 minutes).
- 24 hour planning and execution horizon.
- Bounded, discretized search space.

Optimization algorithm is a modified particle swarm

$$v_{i,t} = \omega v_{i,t-1} + \gamma_1 \phi_1 (p_{i,t-1} - x_{i,t-1}) + \gamma_2 \phi_2 (g_{i,t-1} - x_{i,t-1}) \tag{3}$$

$$x_{i,t} = x_{i,t-1} + v_{i,t} \tag{4}$$

OPTIMIZATION PROCESS

1. Read simulation and weather files.
2. Generate a unique controller and model for each home.
3. For each building, execute the following steps in parallel:
   3.1 Generate candidate decision vector.
   3.2 Simulate planning horizon.
   3.3 Evaluate fitness and exit criteria. Iterate.
4. Write power flow input files.
5. Initiate power flow simulation.

STUDIES

OUTLINE

DEMAND RESPONSE

DESCRIPTION

Residential Demand Response

- Current state of the art in residential demand side management.
- Aimed at reducing demand in the top 2-3% of load duration curve.
- Limited to handful of days out of the year, usually the peak demand days but not always.
- Typically uses programmable communicating thermostats.
- Often voluntary.

CASES

Demand Response cases:

» Worst case scenario.

» Benchmark for comparison.

» Maximum achievable demand reduction.

Methodology

» Two levels of participation: 70% and 30%.

» Two event durations: 2hr and 6hr.

» Simulation day contains annual feeder peak demand.

» Event forces a 2K thermostat offset.

HOUSTON 2HR 70%

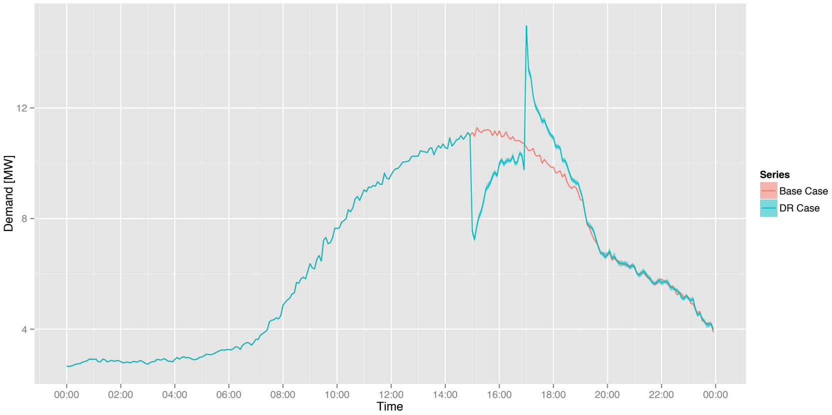


Figure: Houston feeder demand curves for 2hr, 70% DR event.

LOS ANGELES 6HR 70%

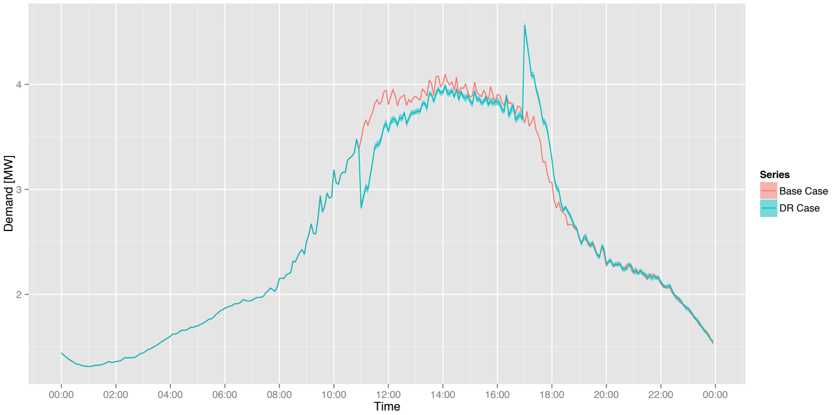


Figure: Los Angeles feeder demand curves for 6hr, 70% DR event.

RESULTS

Table: Performance metrics for three feeders, demand response, 70% and 30% cases.

		Houston		Los Angeles		New York	
		70%	30%	70%	30%	70%	30%
Peak Demand [MW]	2hr	-3.72	-1.58	-0.76	-0.32	-2.00	-0.85
	6hr	-3.26	-1.38	-0.67	-0.28	-1.84	-0.77
Rebound [MW]	2hr	4.39	1.84	0.84	0.37	1.94	0.83
	6hr	4.55	1.90	0.93	0.41	2.12	0.88
Average Demand [MW]	2hr	-1.65	-0.70	-0.39	-0.17	-0.85	-0.36
	6hr	-0.66	-0.28	-0.17	-0.07	-0.35	-0.15

SUMMARY

Demand response results in large peak reductions, but...

» Reductions are not sustained.

» Rebound can be as large or larger than original reduction.

» Rebound is always greater than the reduction in base case peak.

This is an extreme example...

» Participant "staging" can reduce rebound, but not eliminate.

» Ramping down the set point can help to reduce rebound.

» Requires careful planning to avoid new system peak.

DEMAND LIMITING

DESCRIPTION

Demand Limiting Optimization

- » Extremely simple alternative to DR, completely distributed.
- » Objective: minimize demand without creating rebound.
- » Assumes individual optimizations yield aggregate demand reduction.

Methodology

- » Use the distributed MPC scheme to minimize demand at each home.
- » Assume 70% and 30% participation.

OBJECTIVE

Minimize the peak demand in 60-minute simple moving average of house demand:

$$\min \left[\max \left(\{p_j\}_{j=1}^{N-n+1} \right) \right] \tag{5}$$

$$p_j = \frac{1}{n} \sum_{i=j}^{j+n-1} p_i \tag{6}$$

Table: Cooling set point boundary deltas from nominal for demand limiting optimizations. Assumes home is unoccupied between 8:00 and 18:00 $\pm$ 1hr.

	Occupied	Unoccupied
Upper Boundary	+0K	+3K
Lower Boundary	-2K	-5K

HOUSTON DEMAND LIMITING

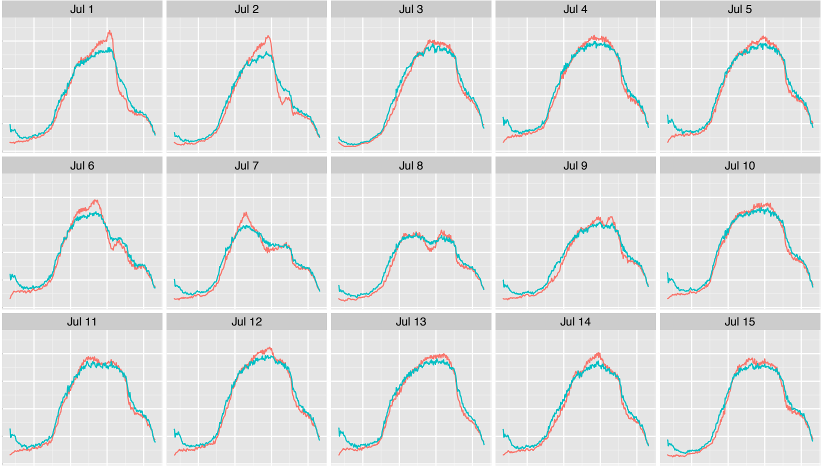


Figure: Feeder demand profiles for Houston demand limiting optimization, 70% participation.

DEMAND REDUCTION

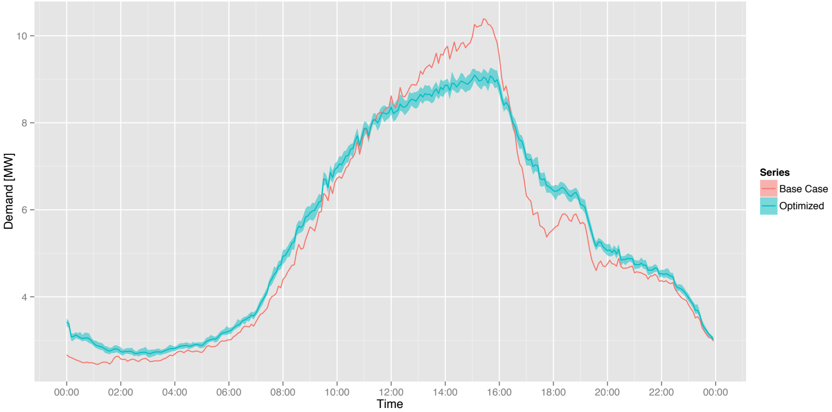


Figure: Feeder demand profiles for Houston, July 02 demand limiting optimization, 70% participation.

RESULTS

Table: Performance metrics for three feeders, demand limiting optimization, 70% and 30% cases.

	Houston		Los Angeles		New York	
	70%	30%	70%	30%	70%	30%
Electric Consumption [MWh]	3.76	1.6	0.62	0.26	1.84	0.8
Peak Demand [MW]	-0.59	-0.26	-0.07	-0.03	-0.22	-0.11
Peak to Valley [%]	81.59	88.36	97.3	98.91	87.39	92.33
Load Factor [%]	5.47	2.3	2.27	0.89	3.93	1.82
Ramp [MW]	-0.61	-0.53	-0.04	-0.02	-0.14	-0.21

STORAGE EFFICIENCY

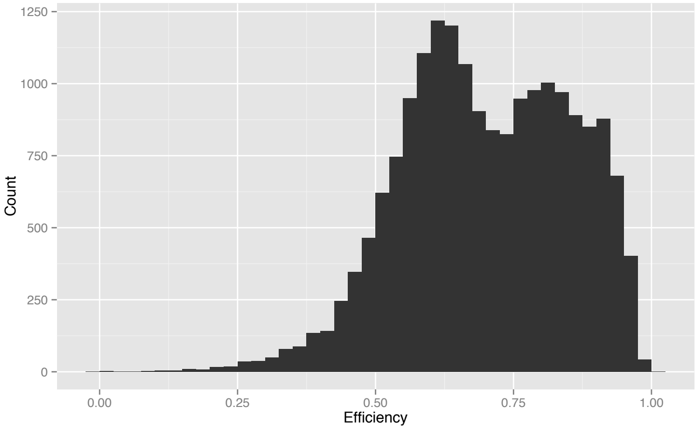


Figure: Histogram showing the thermal storage efficiency of the building envelope from demand limiting optimization of the Los Angeles feeder in July with occupied cooling set point upper boundary.

SUMMARY

Demand limiting very effective:

1. Improvements across the board for most metrics.
2. Increase in electricity consumption related to efficiency of storage.
3. Demand limiting resulted in peak shaving *and* trough filling.
4. No rebound.

A trend emerges:

» 70% > 30%

» Houston > New York > Los Angeles

DAY-AHEAD PRICING

DESCRIPTION

Dynamic pricing as a mechanism for demand management

- Price is a proxy for demand.
- Having homes change operation in anticipation of high price (demand) should result in demand reductions.
- Without price-feedback mechanism, what side-effects result?

Methodology

- Generate day-ahead prices from historical data.
- Have controllers minimize total daily energy cost.
- Assume same 70% and 30% participation.

PRICE MODELING

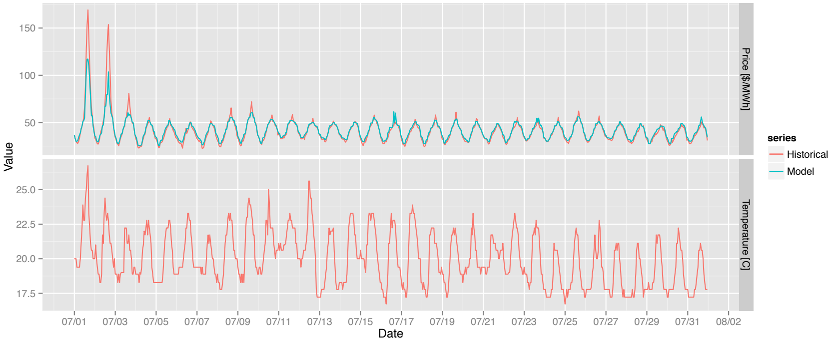


Figure: Historical and modeled CAISO prices using historical weather. Price modeled using classification and regression tree assuming: $log(P) \sim f(T, \Delta T, H, D, W)$

OBJECTIVE

Minimize the total daily cost of electricity given a price signal that varies in time.

$$\min\left(\sum_{i=j}^{k} e_i \cdot c_i\right) \tag{7}$$

Caveats

- Alignment of decision variable *modes* result in step change demand curves.
- Hourly price changes result in synchronization of controller decisions, resulting in oscillations.

UNINTENDED CONSEQUENCES

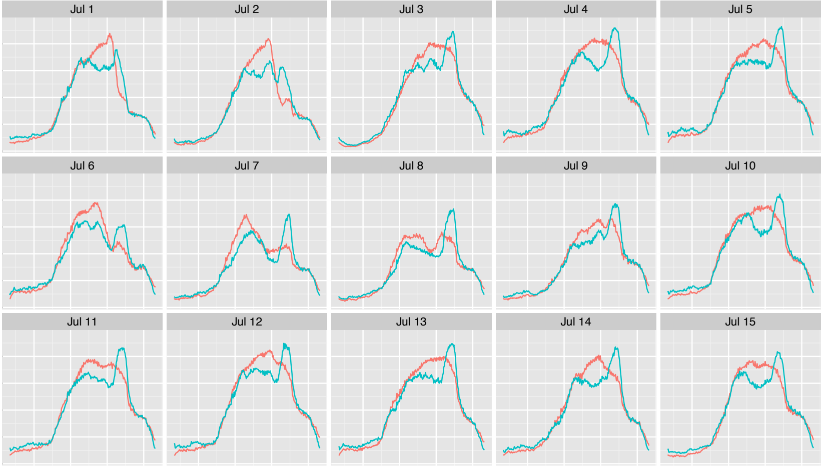


Figure: Feeder demand profiles for Houston day-ahead price optimization, 70% participation.

CONTROLLING THE REBOUND

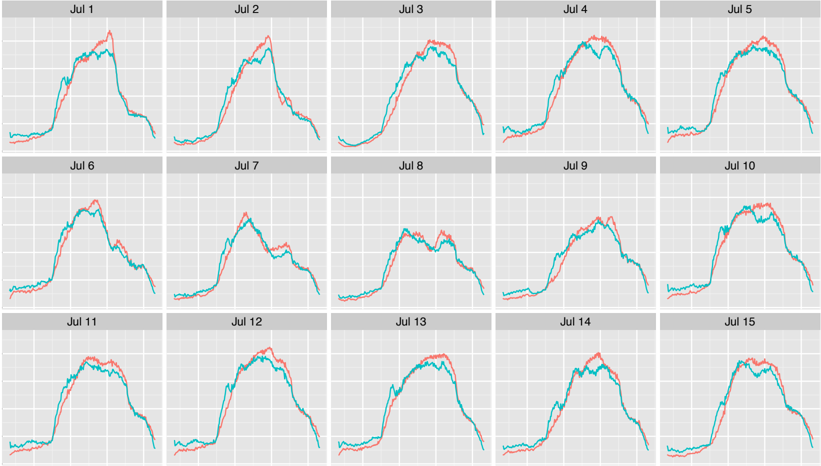


Figure: Feeder demand profiles for Houston day-ahead price optimization, zero-degree upper boundary case, 70% participation.

SYNTHETIC PRICE

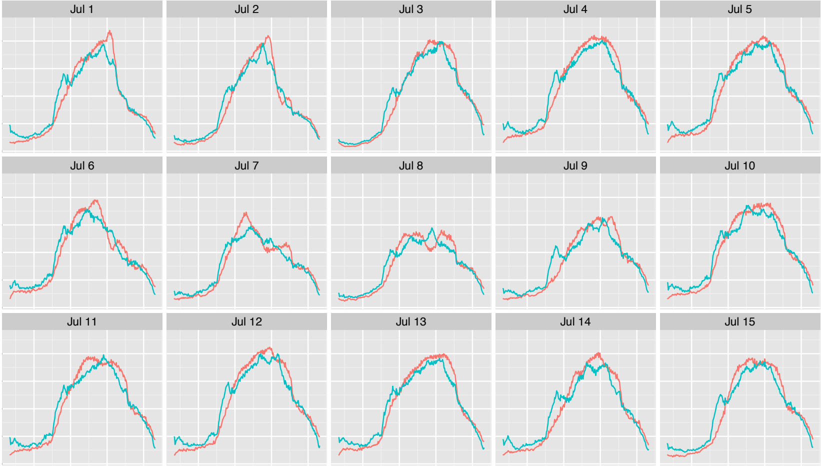


Figure: Feeder demand profiles for Houston synthetic price optimization, zero-degree upper boundary case, 70% participation.

RESULTS

Table: Performance metrics for Houston feeder, dynamic price optimizations; default (DEF), zero-degree (ZD) and ramp-return (RR) upper boundary cases.

	Day-Ahead			Synthetic	
	DEF	ZD	RR	ZD	RR
Electric Consumption [MWh]	-2.01	1.12	-0.99	0.23	-2.08
Peak Demand [MW]	0.36	-0.52	0.12	-0.39	0.36
Peak to Valley [%]	92.95	82.81	88.85	83.77	91.17
Load Factor [%]	-2.85	3.8	-1.05	2.57	-2.94
Ramp [MW]	3.09	0.72	1.93	1.25	2.08

OSCILLATIONS

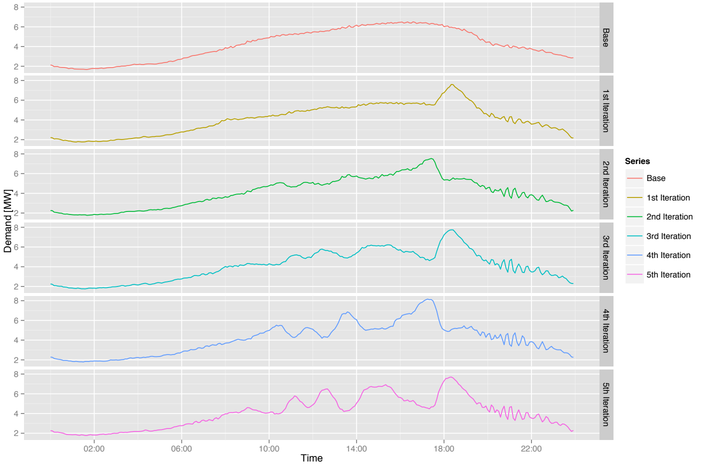


Figure: Oscillations in demand profile created by iteratively supplying feeder demand as electricity price to optimization.

SUMMARY

Dynamic pricing may not be the best signal...

- Results are mixed: some metrics improved, some are not.
- Creates additional variability in feeder demand.
- Can create new peak demand depending on the upper boundary assumptions.
- Not entirely predicable; demand curve is not a obviously related to price.
- Objective function is greedy, not aligned with global objectives.

LOAD SHAPING

DIRECTED OPTIMIZATION

New approach: use distributed optimization scheme but **direct** the optimization using a signal that considers the desired feeder demand.

1. Generate a *reference demand curve* that represents the desired aggregate feeder demand.
2. Transform the feeder reference demand curve into a reference demand curve for each house.
3. Minimize the difference between the house demand curve and *house reference demand curve*.

Tell the homes when to increase or decrease demand

REFERENCE SIGNAL

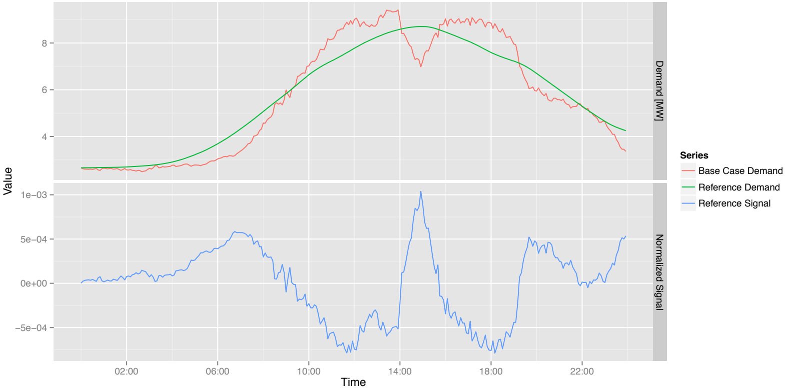


Figure: Example of feeder reference demand and reference signal created from simple moving average of base case feeder demand profile.

OBJECTIVE

Minimize the sum squared error between the *house reference demand curve* and the candidate demand curve.

$$\min \left(\sum_{i=j}^{k} (p'_i - p_i)^2 \right) \tag{8}$$

House reference demand curve

- Base case demand which has been smoothed and normalized.
- Adjusted by reference signal to create a target demand profile.

RESULTS

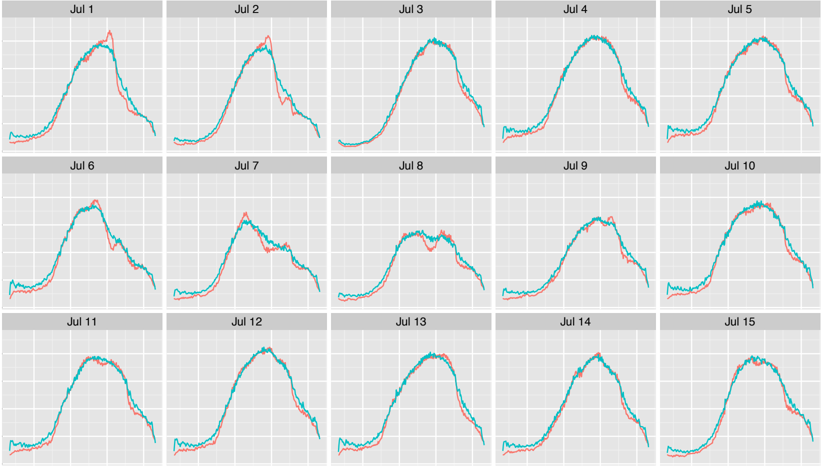


Figure: Feeder demand profiles for Houston load shape optimization, 70% participation.

HOUSTON LOAD SHAPING

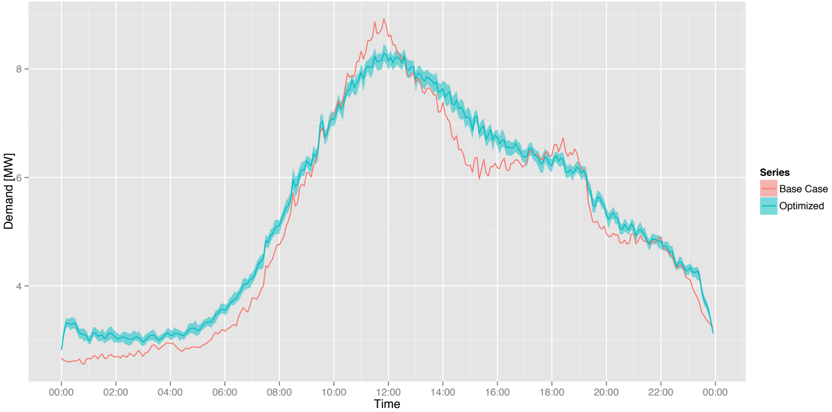


Figure: Feeder demand profiles for Houston, July 07 load shape optimization, 70% participation.

SMOOTHING PEAKS, FILLING TROUGHS

Table: Performance metrics for three feeders, load shaping optimization, 70% and 30% cases.

	Houston		Los Angeles		New York	
	70%	30%	70%	30%	70%	30%
Electric Consumption [MWh]	4.87	2.07	0.70	0.31	2.38	1.03
Peak Demand [MW]	-0.15	-0.09	0.00	0.00	-0.03	-0.02
Peak to Valley [%]	84.26	91.47	99.38	99.62	91.19	95.70
Load Factor [%]	3.02	1.40	0.94	0.48	2.13	1.00
Ramp [MW]	-0.23	-0.59	0.05	-0.02	-0.01	-0.11

SUMMARY

New load shaping methodology

- Shaves peak, fills in troughs as expected.
- Improvements in all metrics except consumption.
- Demand reduction modest, but that wasn't the objective.
- More effective in Houston where there is more "flexible cooling demand".
- Limited by storage efficiency.
- More controlled and predicable than price-based optimization.

ROOFTOP SOLAR

DESCRIPTION

Can variability introduced by rooftop solar be removed through load shaping methodology?

Methodology

- » **Add solar model to reduced order building model.**
- » **Distribute solar to homes according to pre-defined penetration levels.**
- » **Apply load shaping methodology using the feeder demand with solar contribution.**

SOLAR MODEL

Flat plate solar electric model with temperature dependent efficiency and inverter model with part-load efficiency.

$$\eta_c = \eta_0[1 - \beta(T_c - T_0)] \tag{9}$$

$$Q_{DC} = \eta_c I_t A_c \tag{10}$$

$$Q_{AC} = \eta_i \eta_s Q_{DC} \tag{11}$$

Systems sized to offset 80% of a home's annual electricity usage.

MODEL VALIDATION

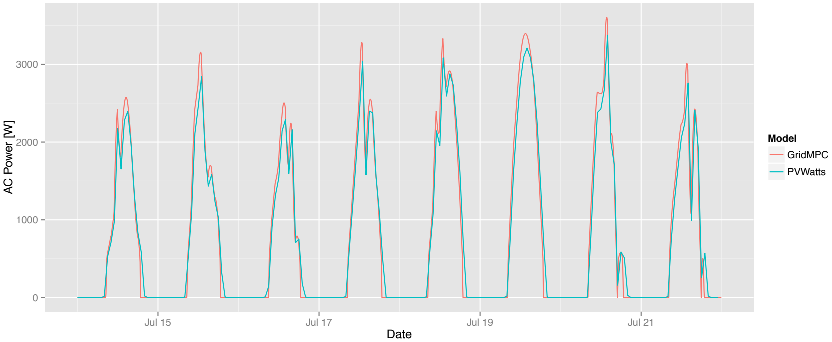


Figure: Example of PV model output compared to PVWatts, July 14-21. Total annual difference between output of models is 1.7%; NRMSE is 8.6%.

LIKE BUTTER

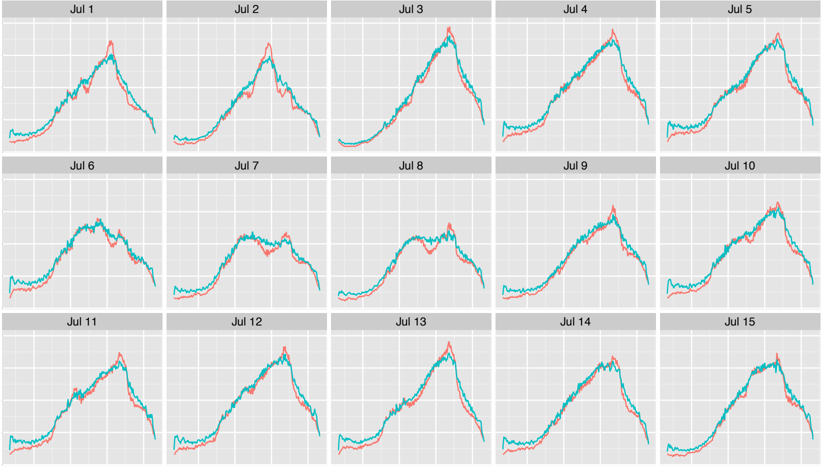


Figure: Feeder demand profiles for Houston load shape optimization, high solar penetration case, 70% participation.

HOUSTON HIGH SOLAR POWER SPECTRUM

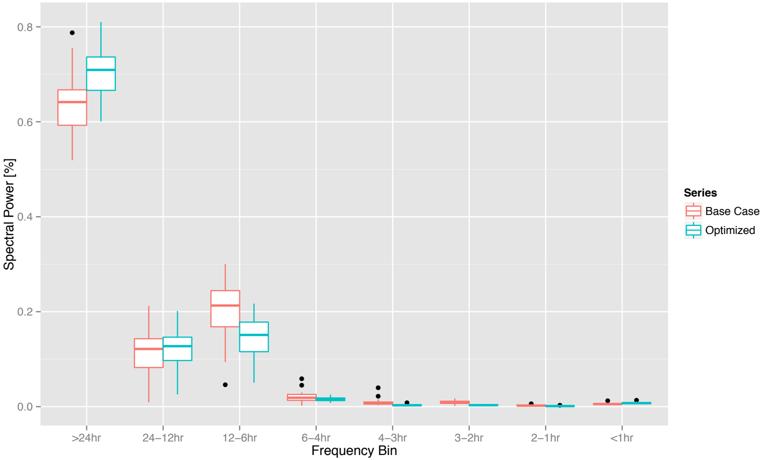


Figure: Total spectral power as a function of frequency bin for Houston feeder load shape optimization, high solar penetration case, 70% participation.

MULTIPLE BENEFITS

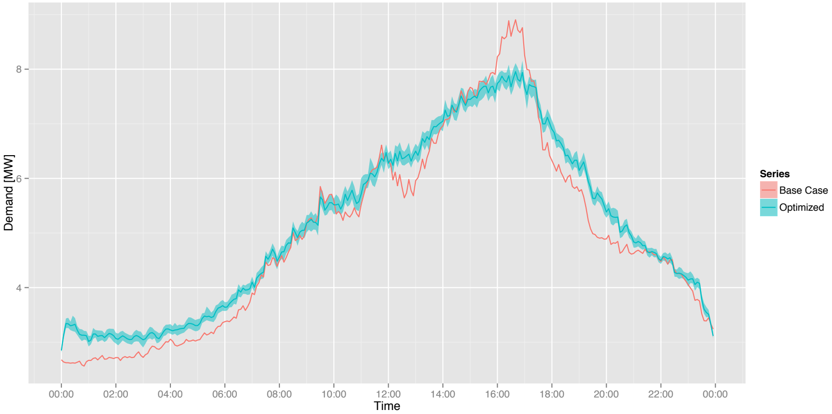


Figure: Feeder demand profiles for Houston, July 01 load shape optimization, high solar penetration case, 70% participation.

LIMITATIONS

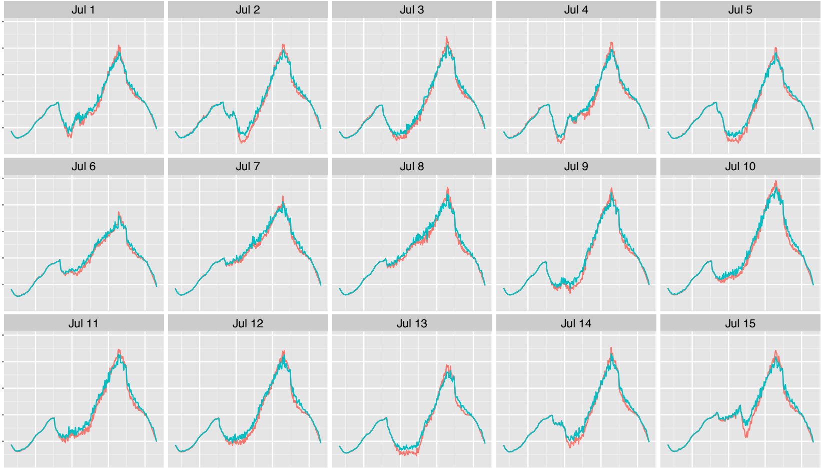


Figure: Feeder demand profiles for Los Angeles load shape optimization, high solar penetration case, 70% participation.

HIGH SOLAR RESULTS

Table: Performance metrics for three feeders, load shaping optimization, high solar, 70% and 30% cases.

	Houston		Los Angeles		New York	
	70%	30%	70%	30%	70%	30%
Electric Consumption [MWh]	4.82	2.07	0.64	0.28	2.32	0.98
Peak Demand [MW]	-0.48	-0.20	-0.10	-0.04	-0.25	-0.10
Peak to Valley [%]	80.04	89.86	95.05	97.34	86.62	93.61
Load Factor [%]	5.85	2.43	2.82	1.20	5.00	2.05
Ramp [MW]	-0.70	-0.77	-0.31	-0.14	-0.47	-0.36

LOW SOLAR RESULTS

Table: Performance metrics for three feeders, load shaping optimization, low solar, 70% and 30% cases.

	Houston		Los Angeles		New York	
	70%	30%	70%	30%	70%	30%
Electric Consumption [MWh]	4.85	2.07	0.68	0.29	2.36	1.01
Peak Demand [MW]	-0.16	-0.10	-0.02	-0.01	-0.03	-0.02
Peak to Valley [%]	84.01	91.05	98.93	99.50	91.11	95.66
Load Factor [%]	3.20	1.60	1.31	0.59	2.17	0.98
Ramp [MW]	-0.31	-0.61	-0.01	-0.02	0.04	-0.18

SUMMARY

With rooftop solar present, load shaping method can:

- » Absorb some of the variability introduced by rooftop solar.
- » Reduce secondary peak.
- » Lessen, but not prevent steep sustained ramp.
- » Provide some protection against over generation.

But...

- » Increased consumption (approx. 5%).
- » Short term shifts appear more effective than long term shifts.
- » Again limited by "flexible cooling demand".

UTILITY-SCALE WIND

DESCRIPTION

Can demand be shaped according to needs outside of the feeder?

- » Wind introduces variability to supply.
- » Variability absorbed by existing generators.
- » High penetration results in curtailment, ramping.

Methodology

- » Simply model contribution of wind outside of distribution feeder.
- » Inject wind production into feeder to create composite demand curve.
- » Apply load shaping methodology using composite feeder demand.

WIND MODELING

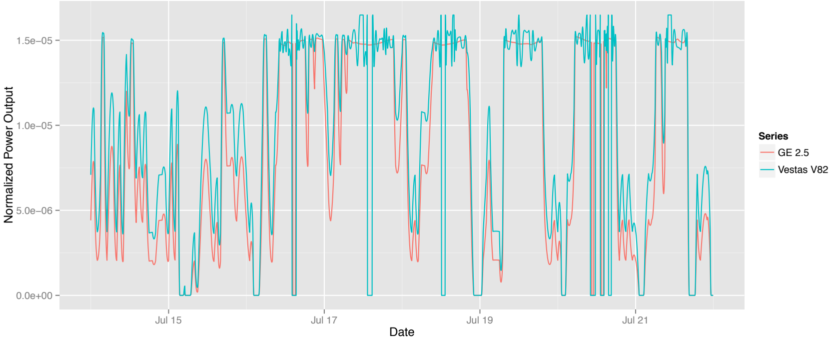


Figure: Normalized wind turbine output for two turbine models showing the difference in output characteristics.

WIND SCALING

To scale normalized turbine output to desired penetration levels:

1. Run turbine model in each of the locations for full year.
2. Normalize annual output to 1MWh.
3. Assume half of wind is contributed by each turbine type.
4. Scale by the factors below:

Table: Scaling factors used for scaling wind turbine output to desired penetration levels of 25% and 9.4%.

	Houston	Los Angeles	New York
25% Penetration [MWh]	10,633	6,425	4,914
9.4% Penetration [MWh]	4,253	2,570	1,966

HOUSTON HIGH WIND

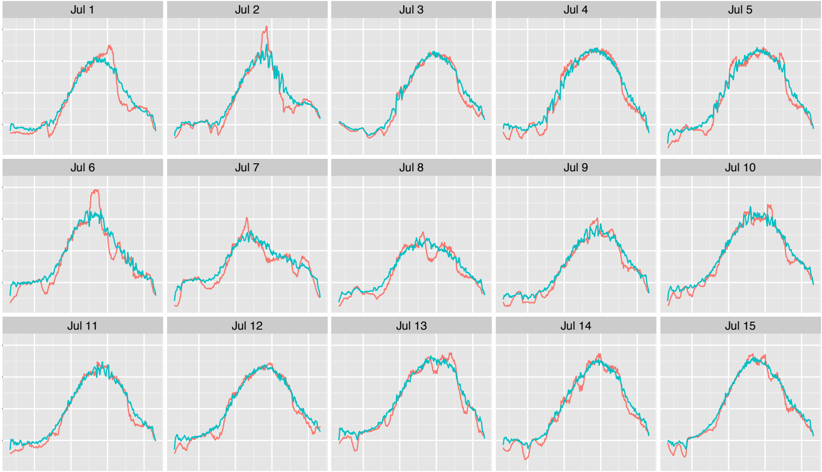


Figure: Feeder demand profiles for Houston load shape optimization, high wind penetration case, 70% participation.

HOUSTON HIGH WIND POWER SPECTRUM

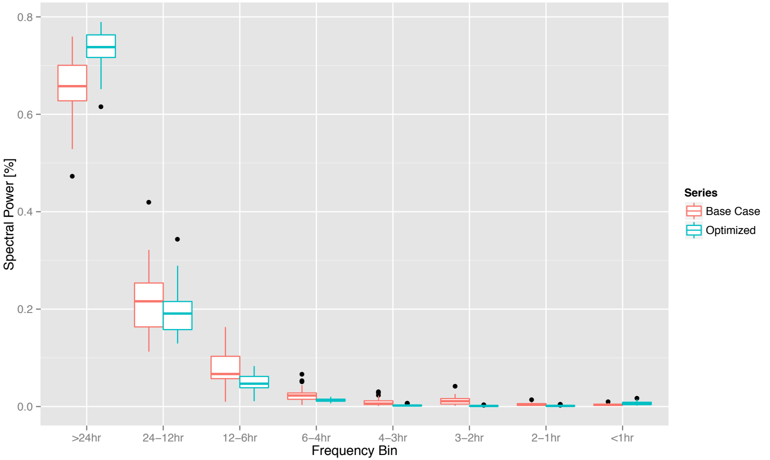


Figure: Total spectral power as a function of frequency bin for Houston feeder load shape optimization, high wind penetration case, 70% participation.

HIGH WIND RESULTS

Table: Performance metrics for three feeders, load shaping optimization, high wind, 70% and 30% cases.

	Houston		Los Angeles		New York	
	70%	30%	70%	30%	70%	30%
Electric Consumption [MWh]	4.80	2.07	0.79	0.34	2.48	1.07
Peak Demand [MW]	-0.50	-0.28	-0.11	-0.05	-0.13	-0.07
Peak to Valley [%]	63.32	77.38	93.09	96.64	79.98	89.05
Load Factor [%]	5.63	2.72	3.65	1.61	3.59	1.72
Ramp [MW]	-2.52	-2.61	-0.44	-0.33	0.26	-0.26

LOW WIND RESULTS

Table: Performance metrics for three feeders, load shaping optimization, low wind, 70% and 30% cases.

	Houston		Los Angeles		New York	
	70%	30%	70%	30%	70%	30%
Electric Consumption [MWh]	4.85	2.09	0.71	0.30	2.44	1.04
Peak Demand [MW]	-0.25	-0.13	-0.04	-0.02	-0.06	-0.03
Peak to Valley [%]	79.75	89.55	97.87	99.02	88.74	94.17
Load Factor [%]	3.78	1.75	1.74	0.80	2.58	1.18
Ramp [MW]	-0.92	-1.11	-0.23	-0.13	0.05	-0.17

SUMMARY

Load shaping methodology shows ability to address needs outside of feeder

- Ability to remove significant variability in composite demand curve.
- Benefits at all levels of participation, penetration.
- Reductions in peak demand.
- Similar limitations as previous cases.

CONCLUSIONS

CONCLUSIONS

Demand Limiting

» Consistent, significant demand reductions

» No rebound effect

Dynamic Price

» Mixed characteristics

» Price-responsive controllers must be carefully designed

» Additional variability under many conditions

Load Shaping

» Very effective at removing variability

» Some demand reductions, could be improved with different reference

» Reduces variability of solar in feeder

» Can be used to absorb variability outside of feeder

CONCLUSIONS

Residential HVAC MPC

- Most effective at short term variations in demand
- Not able to shift demand for long periods
- Methodology can be extended to other loads
- Distributed but directed MPC can be implemented

Limited by

- Flexible cooling demand
- Storage efficiency
- Forecast uncertainty
- Model accuracy

FUTURE WORK

- Short term curtailment and ancillary services
- Effect of weather and load forecast uncertainty
- Model accuracy and fidelity
- Economic and environmental impacts
- Application to battery, EV, micro-grid control