Analytics for Demand Response Optimization in a Microgrid

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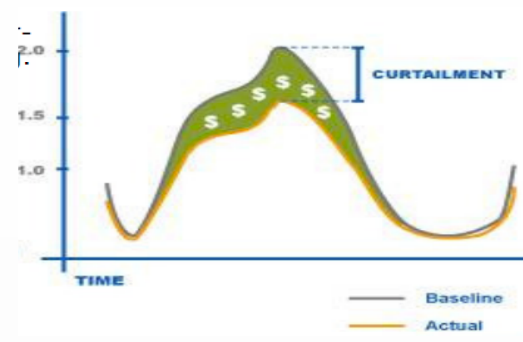
Demand Response – What and Why

Demand Response (DR): Adjustment of electricity consumption during peak load periods in response to a signal from the utility.



Our Research Focus

- Develop reliable forecasting models for consumption and curtailment to assist campus facility managers
- Design Policy Engine for DR optimization on campus
- Map results from campus experiments to city-scale

Benefit of Analytics for Utility	Benefit of Analytics for Customers
• reliably forecast electricity demand • plan generation and supply • implement DR programs • decide time-of-use pricing • determine baselines for curtailment	• interpret historical electricity consumption • adjust consumption according to forecasts • adopt energy-efficient practices • schedule on-site generation • effectively participate in DR programs

Data-driven Analytics

Data Type	Source	Features	Relevance for DR
Electricity Consumption	FMS	15-min; all buildings	Build forecasting models of consumption
Electricity Curtailment	FMS	15-min; few buildings	Build forecasting models of curtailment
Customer Behavior data	CB team	Non-temporal; select group	Model customer participation in DR
Weather data*	Weather Under-ground	hourly; temp. & humidity	Affects consumption & curtailment
Building data*	FMS website	static	Predict consumption & curtailment
Schedule data*	USC calendars	~hourly	Affects consumption & curtailment

*publicly available

Demand Response Policy Engine

Goal: provide decision support for DR:
Determine the following:

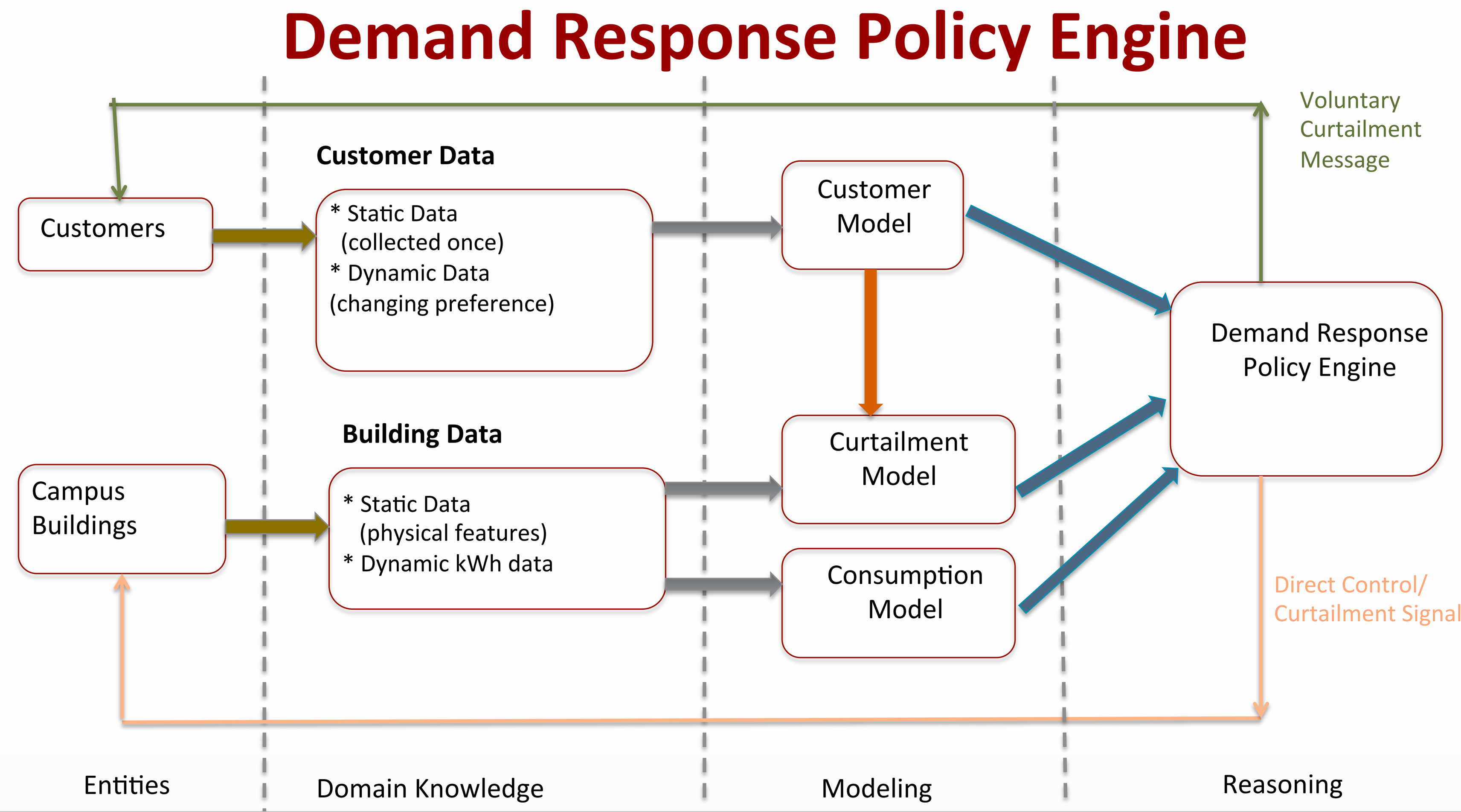
- the buildings for load curtailment
- the subset of customers to target for voluntary curtailment signals
- the set of strategies for individual buildings and customers

Challenges:

- Balance curtailment and comfort levels
- Adapt to changing customer preference
- Some buildings have manager override

Current DR Policies:

- Ad-hoc or heuristics-based
- Address static and short term optimization



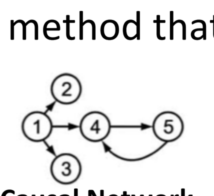
Our Proposed Modeling Approach *(ongoing work)*

- Data-driven approach based on *Markov Decision Processes (MDP)*
- Optimal policy for each building type and customer segment
- Each entity is represented in terms of variables: predicted curtailment, frequency of over and under curtailment, etc.
- Entities are segmented; can migrate between segments based on behavior

Consumption Modeling

Goal: Design, develop, and field ML models that work reliably for following granularities:

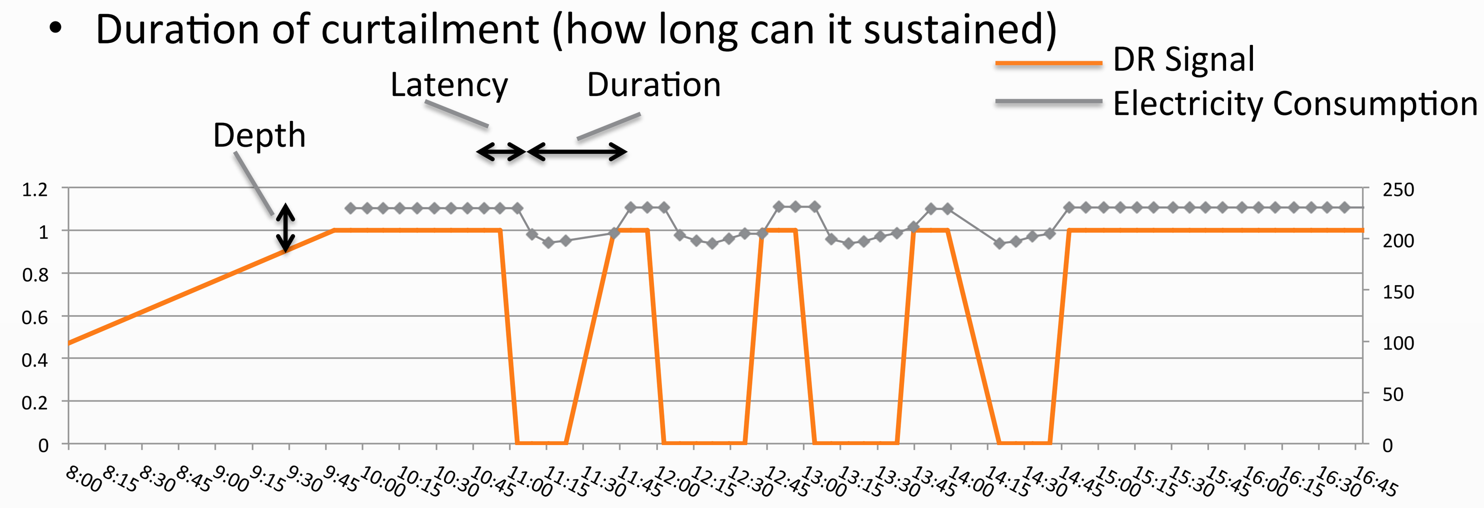
- Temporal: 15-min and Daily
- Spatial: Building-level and Campus-level

Modeling Method	Approach	Pros & Cons
Time-Series Model (Holt-Winters & ARIMA)	Uses previous time series energy use-values to predict future values	• Domain knowledge not required • Addresses variable trends/seasonality • Requires model parameter estimation
Regression Tree Model	Maps a variety of direct and indirect features, X_t to the output, y_t $\{(X_t, y_t)_{t=1}^n\}$	• Time-invariant model • Easy to interpret from domain perspective • Making predictions is fast • Prediction possible with missing data
Our proposed method: Causality-driven Hybrid Model	Maps current features, X_t and regressive values of causative features, α_t, to the output, y_t $\{(\{X_t, \alpha_t\}, y_t)_{t=1}^n\}$ Causative features are found using the *Granger Causality* method that determines causal relation between time series of different features  Causal Network	• Efficient model based on causative features • Better predictive power • Hidden factors not captured • Requires parameter estimation • Time lags affect causality results • Combinatorial explosion with increase in the number of features

Curtailment Modeling

Goal: Determine the following :

- Depth of curtailment (how much can be reduced)
- Latency of curtailment (how soon can it be reduced)
- Duration of curtailment (how long can it sustained)



Building Strategy	Type of Curtailment	Factors affecting curtailment	Modeling approach
Direct Building Control	• Global temperature reset • HVAC Duty-cycling	outdoor temperature occupancy initial physical state type of equipment age of structure	Supervised learning (ongoing work)
Voluntary Customer Control	• turn off lighting • turn off plug-load equipment	Customer participation (voluntary & variable); Customer comfort levels	Markov Chains (ongoing work)

References

1. S.Aman, Y.Simmhan, and V.K.Prasanna. Improving energy use forecast for campus micro-grids using indirect indicators. In Workshop on Domain Driven Data Mining, IEEE, 2011.
2. Y. Simmhan, V. K. Prasanna, S. Aman, S. Natarajan, W. Yin, and Q. Zhou. Towards data-driven demand-response optimization in a campus microgrid. In ACM Workshop On Embedded Sensing Systems For Energy- Efficiency In Buildings. ACM, 2011.
3. S. Aman, W. Yin, Y. Simmhan, and V. K. Prasanna. Machine learning for demand forecasting in smart grid. In Southern California Smart Grid Research Symposium, 2011.
4. Y. Simmhan, S. Aman, B. Cao, M. Giakkoupis, A. Kumbhare, Q. Zhou, D. Paul, C. Fern, A. Sharma, and V. K. Prasanna. An informatics approach to demand response optimization in smart grids. Technical report, 2011.

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