Dynamic Demand Response Optimization in Smart Grids

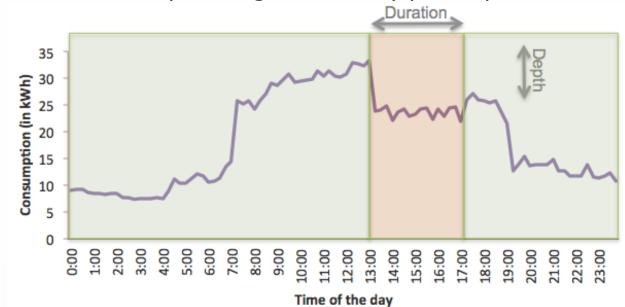
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Dynamic Demand Response (D²R)

Entities

Demand Response (DR):

Adjustment of electricity consumption during peak load periods in response to a signal from the utility through voluntary participation or direct control.



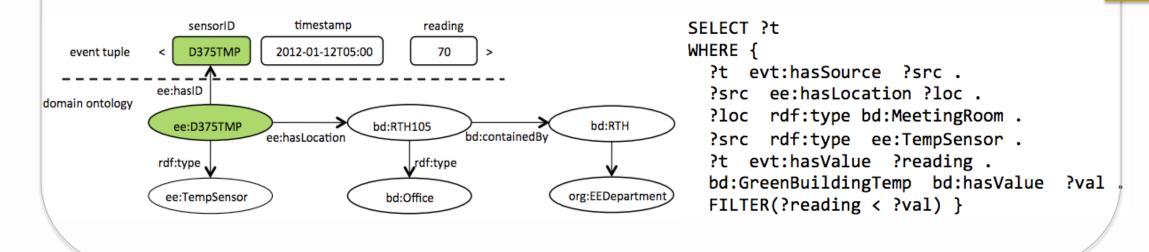
- Information Integration: many, diverse sources
- Data Modeling: machine learning algorithms
- Dynamism:
 - Deviations in achieved voluntary curtailment
 - Fluctuating number of participants
- Scalability:
 - Huge number of customers (~1.4 million customers at city-scale)
 - Large-scale streaming sensory data (~5.6 million data points every hour)

Decision making about when, by how much, and how to reduce electricity consumption curtailment **Customer Data** Curtailment **Prediction Model** (Voluntary Control) **Dynamic Demand** Curtailment **Prediction Model** Policy Engine **Building Data** (Direct Control) Dynamic customer & Static Data strategy selection (physical features) Dynamic kWh and Consumption sensor data **Buildings** 'Space & schedule data **Prediction Model** * Event info Direct curtailment Weather

Information Integration

Challenge: Ingest, parse and semantically annotate sensor data **Approach:**

- 1. Information Integration from diverse sources
- 2. Semantic Information Model for Complex Event processing (CEP)

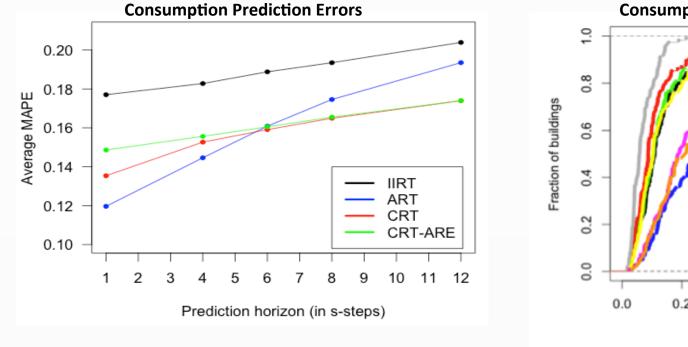


Predictive Modeling

Challenge: Predict consumption and curtailment for individual consumers **Approach:**

Consumption Modeling

- Indirect Indicators based Model (IIRT)
- 2. Time Series based Models (ARIMA and ART)
- 3. Causality based Regression Tree Model (CRT)



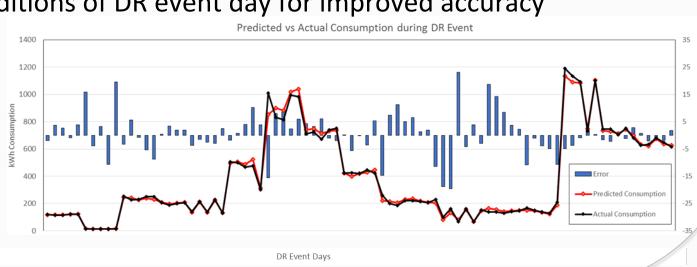
Consumption Prediction Errors Laction of Production Errors CAISO NYISO CASCE ToW TS-1hr TS-4hr TS-24hr RT MAPE MAPE

Curtailment Modeling

- 1. Building–level
 - Curtailment prediction based on similar events (same curtailment strategy)
 - Adjustment to conditions of DR event day for improved accuracy

 Predicted vs Actual Consumption during DR Event

2. Equipment-level: Bottom-Up prediction based on equipment curtailment modeling



Dynamic Decision Making

Challenge: Automated DR decision support Approach:

DDS (Demand Response Decision Support System):

- DR Decision Support System : http://smartgrid.usc.edu/dds-javadoc/
- DR Scheduling Engine: http://smartgrid.usc.edu/sgpe/

Scalability

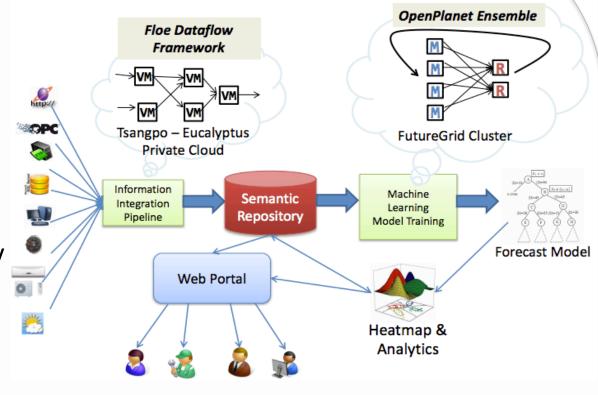
Predictive Modeling

Information Integration

Dynamic Demand response (D²R):

- 1. Floe: Continuous data flow framework using Eucalyptus
 Private Cloud
- 2. Streaming CEP: interactive query processing over real-time data

Information Integration



Dynamic Decision making

Data-driven Demand Prediction Modeling

- 1. OpenPlanet MapReduce based algorithm for regression tree training
- 2. Scalable prediction using Incremental clustering:
 - Customers grouped into virtual customers
 - Incremental addition based on reduction in cluster prediction error

Randomly chosen Cn C3 C2 C1 Decision $S_1' = S_1 + C1$ $E_1 = ARIMA(S_1') \cdot Error$ $S_2' = S_2 + C1$ $E_2 = ARIMA(S_2') \cdot Error$ Customer Time Series $S_x = Min(E1, E2, E3) \cdot Bin$ $S_x = S_x + C1$

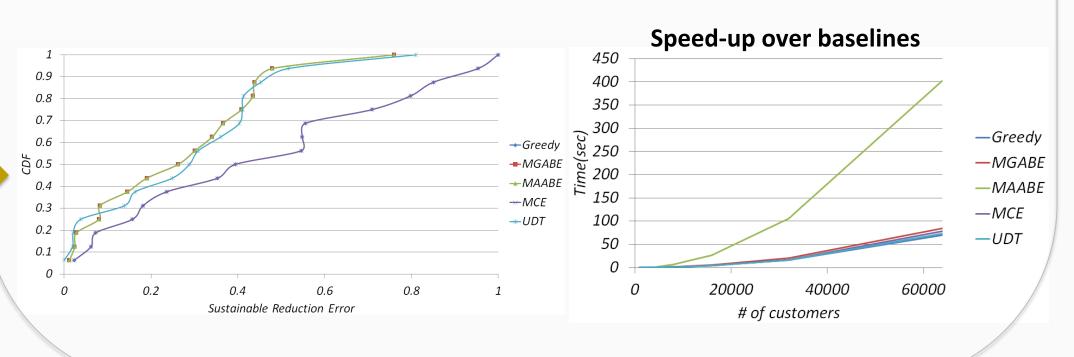
3. Leveraging Big Data for Scalable Prediction

Build prediction models for representative customers using real time data and extrapolate for *similar* customers



Efficient Customer Selection for DR:

- Scalable Greedy Algorithm to select <customer-strategy> combinations
- Sustainable consistent reduction between consecutive customer re-selections
- Minimum number of participants selected to achieve a target curtailment



University of Southern California